Deep Learning Seminar - Final-Copy2

February 20, 2024

1 Deep Learning Seminar

1.1 House Price Prediction with Neural Network

[1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import seaborn as sns
```

1.1.1 Data Reading and Data Overview

[2]:
```python
train_hpp = pd.read_csv ("C:/Users/ZulkifliIndraGadingC/OneDrive/HTW/DL/Project/
↪train.csv")
```

[3]:
```python
train_hpp.head()
```

[3]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave   NaN      Reg
1   2          20       RL         80.0     9600   Pave   NaN      Reg
2   3          60       RL         68.0    11250   Pave   NaN      IR1
3   4          70       RL         60.0     9550   Pave   NaN      IR1
4   5          60       RL         84.0    14260   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
1         Lvl    AllPub  …        0    NaN   NaN         NaN       0      5
2         Lvl    AllPub  …        0    NaN   NaN         NaN       0      9
3         Lvl    AllPub  …        0    NaN   NaN         NaN       0      2
4         Lvl    AllPub  …        0    NaN   NaN         NaN       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000
```

```
[5 rows x 81 columns]
```

[4]:
```python
train_hpp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1460 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1460 non-null   int64
 1   MSSubClass     1460 non-null   int64
 2   MSZoning       1460 non-null   object
 3   LotFrontage    1201 non-null   float64
 4   LotArea        1460 non-null   int64
 5   Street         1460 non-null   object
 6   Alley          91 non-null     object
 7   LotShape       1460 non-null   object
 8   LandContour    1460 non-null   object
 9   Utilities      1460 non-null   object
 10  LotConfig      1460 non-null   object
 11  LandSlope      1460 non-null   object
 12  Neighborhood   1460 non-null   object
 13  Condition1     1460 non-null   object
 14  Condition2     1460 non-null   object
 15  BldgType       1460 non-null   object
 16  HouseStyle     1460 non-null   object
 17  OverallQual    1460 non-null   int64
 18  OverallCond    1460 non-null   int64
 19  YearBuilt      1460 non-null   int64
 20  YearRemodAdd   1460 non-null   int64
 21  RoofStyle      1460 non-null   object
 22  RoofMatl       1460 non-null   object
 23  Exterior1st    1460 non-null   object
 24  Exterior2nd    1460 non-null   object
 25  MasVnrType     588 non-null    object
 26  MasVnrArea     1452 non-null   float64
 27  ExterQual      1460 non-null   object
 28  ExterCond      1460 non-null   object
 29  Foundation     1460 non-null   object
 30  BsmtQual       1423 non-null   object
 31  BsmtCond       1423 non-null   object
 32  BsmtExposure   1422 non-null   object
 33  BsmtFinType1   1423 non-null   object
 34  BsmtFinSF1     1460 non-null   int64
 35  BsmtFinType2   1422 non-null   object
 36  BsmtFinSF2     1460 non-null   int64
 37  BsmtUnfSF      1460 non-null   int64
 38  TotalBsmtSF    1460 non-null   int64
```

```
 39  Heating        1460 non-null   object
 40  HeatingQC      1460 non-null   object
 41  CentralAir     1460 non-null   object
 42  Electrical     1459 non-null   object
 43  1stFlrSF       1460 non-null   int64
 44  2ndFlrSF       1460 non-null   int64
 45  LowQualFinSF   1460 non-null   int64
 46  GrLivArea      1460 non-null   int64
 47  BsmtFullBath   1460 non-null   int64
 48  BsmtHalfBath   1460 non-null   int64
 49  FullBath       1460 non-null   int64
 50  HalfBath       1460 non-null   int64
 51  BedroomAbvGr   1460 non-null   int64
 52  KitchenAbvGr   1460 non-null   int64
 53  KitchenQual    1460 non-null   object
 54  TotRmsAbvGrd   1460 non-null   int64
 55  Functional     1460 non-null   object
 56  Fireplaces     1460 non-null   int64
 57  FireplaceQu    770 non-null    object
 58  GarageType     1379 non-null   object
 59  GarageYrBlt    1379 non-null   float64
 60  GarageFinish   1379 non-null   object
 61  GarageCars     1460 non-null   int64
 62  GarageArea     1460 non-null   int64
 63  GarageQual     1379 non-null   object
 64  GarageCond     1379 non-null   object
 65  PavedDrive     1460 non-null   object
 66  WoodDeckSF     1460 non-null   int64
 67  OpenPorchSF    1460 non-null   int64
 68  EnclosedPorch  1460 non-null   int64
 69  3SsnPorch      1460 non-null   int64
 70  ScreenPorch    1460 non-null   int64
 71  PoolArea       1460 non-null   int64
 72  PoolQC         7 non-null      object
 73  Fence          281 non-null    object
 74  MiscFeature    54 non-null     object
 75  MiscVal        1460 non-null   int64
 76  MoSold         1460 non-null   int64
 77  YrSold         1460 non-null   int64
 78  SaleType       1460 non-null   object
 79  SaleCondition  1460 non-null   object
 80  SalePrice      1460 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 924.0+ KB
```

Grouping the features based on their data type

```
[5]: #int, number but categorical
int_columns = ["OverallQual", "OverallCond", "YearBuilt", "YearRemodAdd",␣
 ↪"BsmtFullBath", "BsmtHalfBath",
               "FullBath", "HalfBath", "BedroomAbvGr", "KitchenAbvGr",␣
 ↪"TotRmsAbvGrd", "Fireplaces",
               "GarageYrBlt", "GarageCars", "MoSold", "YrSold"]

#float or area
float_columns = ["LotFrontage", "LotArea", "MasVnrArea", "BsmtFinSF1",␣
 ↪"BsmtFinSF2", "BsmtUnfSF",
                 "TotalBsmtSF", "1stFlrSF", "2ndFlrSF", "LowQualFinSF",␣
 ↪"GrLivArea", "GarageArea",
                 "WoodDeckSF", "OpenPorchSF", "EnclosedPorch", "3SsnPorch",␣
 ↪"ScreenPorch", "PoolArea","MiscVal"]

#categorical with order
ordinal_columns = ["OverallQual", "OverallCond", "YearBuilt", "YearRemodAdd",␣
 ↪"BsmtQual", "BsmtCond",
                   "BsmtExposure", "BsmtFinType1", "BsmtFinType2", "HeatingQC",␣
 ↪"CentralAir", "KitchenQual",
                   "FireplaceQu", "GarageFinish", "GarageQual", "GarageCond",␣
 ↪"PavedDrive", "PoolQC",
                   "Fence"]

#categorical without order (obj and int datatype)
obj_columns = ["MSSubClass", "MSZoning", "Street", "Alley", "LotShape",␣
 ↪"LandContour",
               "Utilities", "LotConfig", "LandSlope", "Neighborhood",␣
 ↪"Condition1", "Condition2",
               "BldgType", "HouseStyle", "RoofStyle", "RoofMatl",␣
 ↪"Exterior1st", "Exterior2nd",
               "MasVnrType", "ExterQual", "ExterCond", "Foundation", "Heating",␣
 ↪"Electrical",
               "Functional", "GarageType", "MiscFeature", "SaleType",␣
 ↪"SaleCondition"]
```

1.1.2 Missing Value

```
[6]: # See the columns with missing value
train_hpp.isna().sum()[train_hpp.isna().sum() > 0].sort_values(ascending =␣
 ↪False)
```

```
[6]: PoolQC          1453
     MiscFeature     1406
     Alley           1369
     Fence           1179
```

```
MasVnrType       872
FireplaceQu      690
LotFrontage      259
GarageType        81
GarageYrBlt       81
GarageFinish      81
GarageQual        81
GarageCond        81
BsmtFinType2      38
BsmtExposure      38
BsmtFinType1      37
BsmtCond          37
BsmtQual          37
MasVnrArea         8
Electrical         1
dtype: int64
```

Handling Missing Value Not all missing value are missing value. Sometimes it means it doesn't have something (value = 0 or none)

[7]:
```
#Column with true missing value only Electrical, GarageYrBlt and LotFrontage
cat_false_na = ["MasVnrType", "FireplaceQu", "GarageType", "GarageFinish",␣
 ↪"GarageQual",
           "GarageCond", "BsmtFinType2", "BsmtExposure", "BsmtFinType1",␣
 ↪"BsmtCond", "BsmtQual",
           "MasVnrArea", "PoolQC", "MiscFeature", "Alley", "Fence"]#,␣
 ↪"Fireplaces"]
```

Handling false NA in numerical data type

[8]:
```
#Impute 0 in MasVnrArea
train_hpp["MasVnrArea"] = train_hpp["MasVnrArea"].fillna(value = 0, inplace =␣
 ↪False)
```

Handling false NA in categorical data type

[9]:
```
#Fillna with None
train_hpp[cat_false_na] = train_hpp[cat_false_na].fillna(value = "None",␣
 ↪inplace = False)

#Check isna
train_hpp.isna().sum()[train_hpp.isna().sum() > 0].sort_values(ascending =␣
 ↪False)
```

[9]:
```
LotFrontage    259
GarageYrBlt     81
Electrical       1
dtype: int64
```

Handling true missing value

[10]:
```
#Drop electrical
train_hpp.dropna(subset = ["Electrical"], inplace = True)

#Imputing LotFrontage with median
train_hpp["LotFrontage"] = train_hpp["LotFrontage"].
↪fillna(train_hpp["LotFrontage"].median())

#Imputing GarageYrBlt with median
train_hpp["GarageYrBlt"] = train_hpp["GarageYrBlt"].
↪fillna(train_hpp["GarageYrBlt"].median())

#Check isna
train_hpp.isna().sum()[train_hpp.isna().sum() > 0].sort_values(ascending =␣
↪False)
```

[10]:
```
Series([], dtype: int64)
```

[11]:
```
# reset index
#train_hpp.reset_index(drop = True, inplace = True)
```

[12]:
```
train_hpp.head()
```

[12]:
```
   Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0   1          60       RL         65.0     8450   Pave  None      Reg
1   2          20       RL         80.0     9600   Pave  None      Reg
2   3          60       RL         68.0    11250   Pave  None      IR1
3   4          70       RL         60.0     9550   Pave  None      IR1
4   5          60       RL         84.0    14260   Pave  None      IR1

  LandContour Utilities  … PoolArea PoolQC Fence MiscFeature MiscVal MoSold  \
0         Lvl    AllPub  …        0   None  None        None       0      2
1         Lvl    AllPub  …        0   None  None        None       0      5
2         Lvl    AllPub  …        0   None  None        None       0      9
3         Lvl    AllPub  …        0   None  None        None       0      2
4         Lvl    AllPub  …        0   None  None        None       0     12

  YrSold  SaleType  SaleCondition  SalePrice
0   2008        WD         Normal     208500
1   2007        WD         Normal     181500
2   2008        WD         Normal     223500
3   2006        WD        Abnorml     140000
4   2008        WD         Normal     250000

[5 rows x 81 columns]
```

[13]:
```
train_hpp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1459 entries, 0 to 1459
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1459 non-null   int64
 1   MSSubClass     1459 non-null   int64
 2   MSZoning       1459 non-null   object
 3   LotFrontage    1459 non-null   float64
 4   LotArea        1459 non-null   int64
 5   Street         1459 non-null   object
 6   Alley          1459 non-null   object
 7   LotShape       1459 non-null   object
 8   LandContour    1459 non-null   object
 9   Utilities      1459 non-null   object
 10  LotConfig      1459 non-null   object
 11  LandSlope      1459 non-null   object
 12  Neighborhood   1459 non-null   object
 13  Condition1     1459 non-null   object
 14  Condition2     1459 non-null   object
 15  BldgType       1459 non-null   object
 16  HouseStyle     1459 non-null   object
 17  OverallQual    1459 non-null   int64
 18  OverallCond    1459 non-null   int64
 19  YearBuilt      1459 non-null   int64
 20  YearRemodAdd   1459 non-null   int64
 21  RoofStyle      1459 non-null   object
 22  RoofMatl       1459 non-null   object
 23  Exterior1st    1459 non-null   object
 24  Exterior2nd    1459 non-null   object
 25  MasVnrType     1459 non-null   object
 26  MasVnrArea     1459 non-null   float64
 27  ExterQual      1459 non-null   object
 28  ExterCond      1459 non-null   object
 29  Foundation     1459 non-null   object
 30  BsmtQual       1459 non-null   object
 31  BsmtCond       1459 non-null   object
 32  BsmtExposure   1459 non-null   object
 33  BsmtFinType1   1459 non-null   object
 34  BsmtFinSF1     1459 non-null   int64
 35  BsmtFinType2   1459 non-null   object
 36  BsmtFinSF2     1459 non-null   int64
 37  BsmtUnfSF      1459 non-null   int64
 38  TotalBsmtSF    1459 non-null   int64
 39  Heating        1459 non-null   object
 40  HeatingQC      1459 non-null   object
 41  CentralAir     1459 non-null   object
 42  Electrical     1459 non-null   object
```

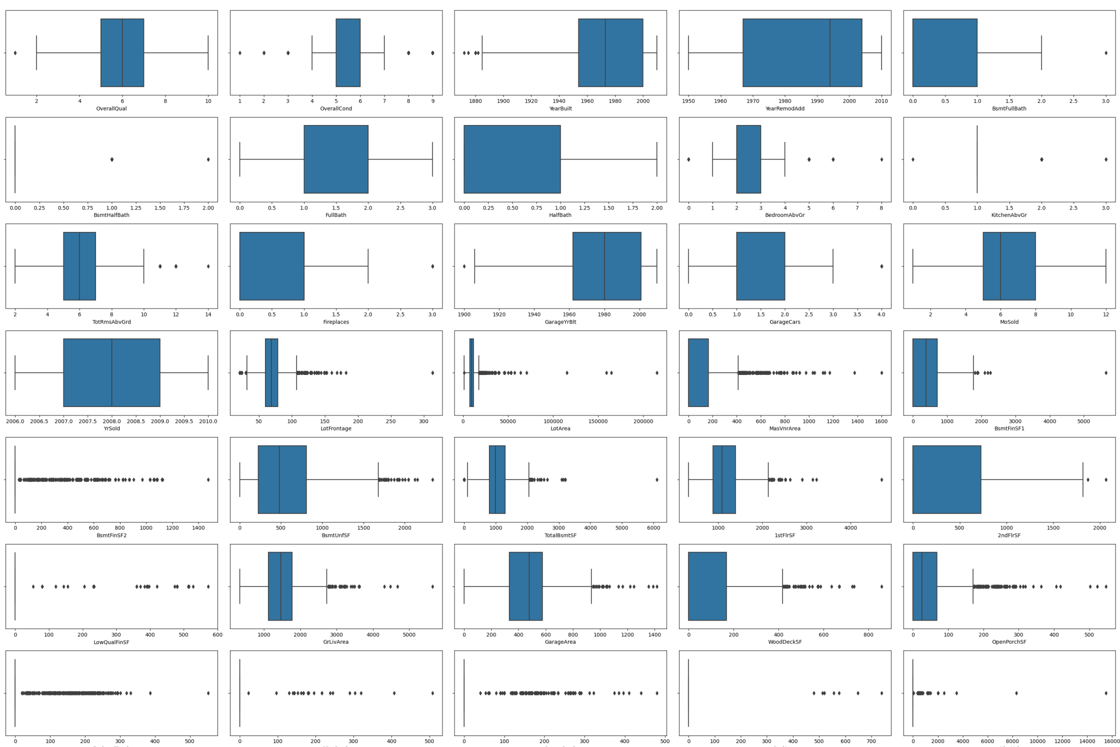
```
 43  1stFlrSF       1459 non-null   int64
 44  2ndFlrSF       1459 non-null   int64
 45  LowQualFinSF   1459 non-null   int64
 46  GrLivArea      1459 non-null   int64
 47  BsmtFullBath   1459 non-null   int64
 48  BsmtHalfBath   1459 non-null   int64
 49  FullBath       1459 non-null   int64
 50  HalfBath       1459 non-null   int64
 51  BedroomAbvGr   1459 non-null   int64
 52  KitchenAbvGr   1459 non-null   int64
 53  KitchenQual    1459 non-null   object
 54  TotRmsAbvGrd   1459 non-null   int64
 55  Functional     1459 non-null   object
 56  Fireplaces     1459 non-null   int64
 57  FireplaceQu    1459 non-null   object
 58  GarageType     1459 non-null   object
 59  GarageYrBlt    1459 non-null   float64
 60  GarageFinish   1459 non-null   object
 61  GarageCars     1459 non-null   int64
 62  GarageArea     1459 non-null   int64
 63  GarageQual     1459 non-null   object
 64  GarageCond     1459 non-null   object
 65  PavedDrive     1459 non-null   object
 66  WoodDeckSF     1459 non-null   int64
 67  OpenPorchSF    1459 non-null   int64
 68  EnclosedPorch  1459 non-null   int64
 69  3SsnPorch      1459 non-null   int64
 70  ScreenPorch    1459 non-null   int64
 71  PoolArea       1459 non-null   int64
 72  PoolQC         1459 non-null   object
 73  Fence          1459 non-null   object
 74  MiscFeature    1459 non-null   object
 75  MiscVal        1459 non-null   int64
 76  MoSold         1459 non-null   int64
 77  YrSold         1459 non-null   int64
 78  SaleType       1459 non-null   object
 79  SaleCondition  1459 non-null   object
 80  SalePrice      1459 non-null   int64
dtypes: float64(3), int64(35), object(43)
memory usage: 934.7+ KB
```

1.1.3 Outlier

[14]:
```
# all numeric columns
num_col = int_columns + float_columns

# Select only numerical features
```

```
num_features = train_hpp[num_col]
```

[15]:
```
# See outlier with boxplot
# Layout of the plot
fig, axes = plt.subplots(nrows = 7, ncols = 5, figsize = (30,20))
axes = axes.flatten()

for i, col in enumerate(num_features.columns):
    if i < len(num_features):
        sns.boxplot(x = train_hpp[col], ax = axes[i])

for i in range(len(num_features.columns), len(axes)):
    fig.delaxes(axes[i])

plt.tight_layout()
plt.show()
```



Handling Outlier

[16]:
```
#Droping column, thorse q1, q2 and q3 are zero.
train_hpp = train_hpp.drop(columns = ["BsmtFinSF2", "LowQualFinSF",␣
↪"EnclosedPorch", "3SsnPorch",
                                      "ScreenPorch", "PoolArea", "MiscVal"])
```

[17]:
```
#Outlier Column
outlier_cols = ["LotFrontage", "LotArea", "MasVnrArea", "BsmtFinSF1",␣
↪"BsmtUnfSF", "TotalBsmtSF",
                 "1stFlrSF", "2ndFlrSF", "GrLivArea", "GarageArea",␣
↪"WoodDeckSF", "OpenPorchSF"]
```

[18]:
```
#change the outlier column datatype to float
train_hpp[outlier_cols] = train_hpp[outlier_cols].astype(float)

#check info
train_hpp[outlier_cols].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1459 entries, 0 to 1459
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   LotFrontage  1459 non-null   float64
 1   LotArea      1459 non-null   float64
 2   MasVnrArea   1459 non-null   float64
 3   BsmtFinSF1   1459 non-null   float64
 4   BsmtUnfSF    1459 non-null   float64
 5   TotalBsmtSF  1459 non-null   float64
 6   1stFlrSF     1459 non-null   float64
 7   2ndFlrSF     1459 non-null   float64
 8   GrLivArea    1459 non-null   float64
 9   GarageArea   1459 non-null   float64
 10  WoodDeckSF   1459 non-null   float64
 11  OpenPorchSF  1459 non-null   float64
dtypes: float64(12)
memory usage: 148.2 KB
```

[19]:
```
#Change the outlier value with IQR Methode

def handle_outliers_iqr(dataframe, column):
    Q1 = dataframe[column].quantile(0.25)
    Q3 = dataframe[column].quantile(0.75)
    IQR = Q3 - Q1

    lower = Q1 - 1.5 * IQR
    upper = Q3 + 1.5 * IQR

    dataframe.loc[(dataframe[col] > upper,col)]=upper
    dataframe.loc[(dataframe[col] < lower,col)]=lower

    return dataframe
```

```
for col in train_hpp[outlier_cols].columns :
    train_hpp = handle_outliers_iqr(train_hpp, col)

train_hpp[outlier_cols]
```

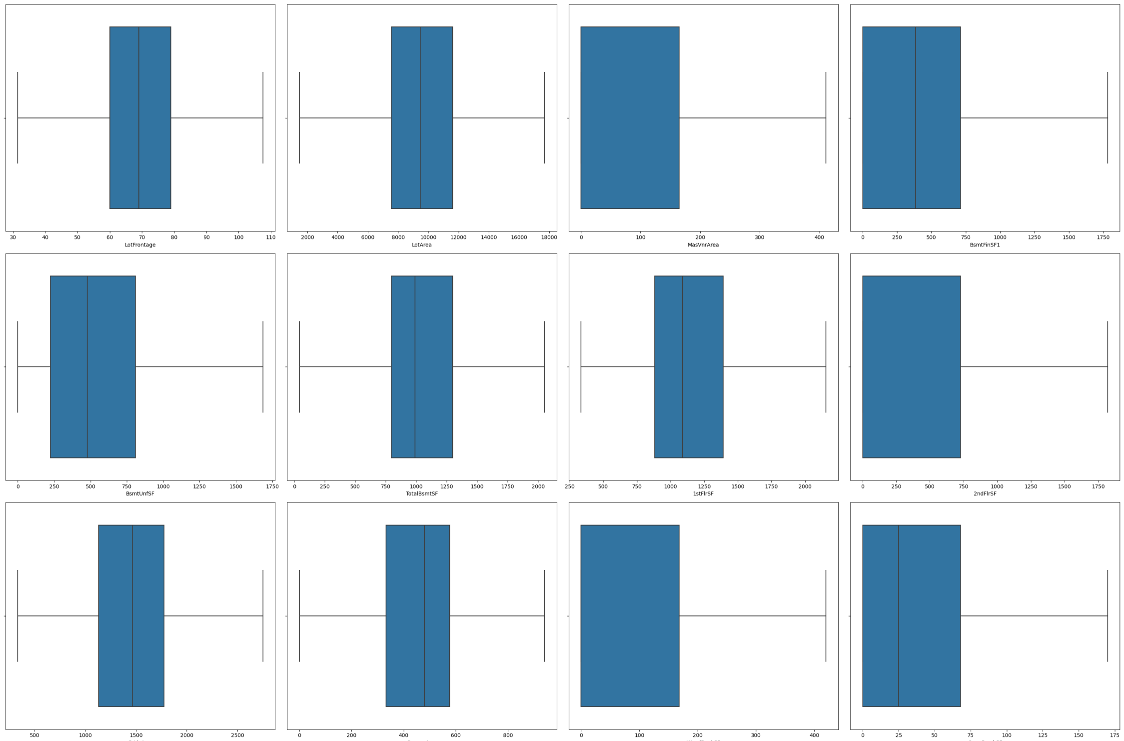
[19]:

```
      LotFrontage  LotArea  MasVnrArea  BsmtFinSF1  BsmtUnfSF  TotalBsmtSF  \
0            65.0   8450.0       196.0       706.0      150.0        856.0
1            80.0   9600.0         0.0       978.0      284.0       1262.0
2            68.0  11250.0       162.0       486.0      434.0        920.0
3            60.0   9550.0         0.0       216.0      540.0        756.0
4            84.0  14260.0       350.0       655.0      490.0       1145.0
…             …        …          …           …          …            …
1455         62.0   7917.0         0.0         0.0      953.0        953.0
1456         85.0  13175.0       119.0       790.0      589.0       1542.0
1457         66.0   9042.0         0.0       275.0      877.0       1152.0
1458         68.0   9717.0         0.0        49.0        0.0       1078.0
1459         75.0   9937.0         0.0       830.0      136.0       1256.0

      1stFlrSF  2ndFlrSF  GrLivArea  GarageArea  WoodDeckSF  OpenPorchSF
0        856.0     854.0     1710.0       548.0         0.0         61.0
1       1262.0       0.0     1262.0       460.0       298.0          0.0
2        920.0     866.0     1786.0       608.0         0.0         42.0
3        961.0     756.0     1717.0       642.0         0.0         35.0
4       1145.0    1053.0     2198.0       836.0       192.0         84.0
…          …         …          …           …           …            …
1455     953.0     694.0     1647.0       460.0         0.0         40.0
1456    2073.0       0.0     2073.0       500.0       349.0          0.0
1457    1188.0    1152.0     2340.0       252.0         0.0         60.0
1458    1078.0       0.0     1078.0       240.0       366.0          0.0
1459    1256.0       0.0     1256.0       276.0       420.0         68.0

[1459 rows x 12 columns]
```

[20]:

```
#check with boxplot
outlier_df = train_hpp[outlier_cols]

fig, axes = plt.subplots(nrows = 3, ncols = 4, figsize = (30,20))
axes = axes.flatten()

for i, col in enumerate(outlier_df.columns):
    if i < len(outlier_df):
        sns.boxplot(x = train_hpp[col], ax = axes[i])

for i in range(len(num_features.columns), len(axes)):
    fig.delaxes(axes[i])

plt.tight_layout()
```

```python
plt.show()
```



1.1.4 Encoding for categorical features

[21]:
```python
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import OneHotEncoder
```

[22]:
```python
#checking categorical features
cat = train_hpp.select_dtypes(include = "O").keys()
cat
len(cat)
```

[22]: 43

Encoding the categorical features without order

[23]:
```python
cat_non_ordinal = ["MSSubClass", "MSZoning", "Street", "LotShape",␣
↪"LandContour", "Utilities",
                   "LotConfig", "LandSlope","Neighborhood", "Condition1",␣
↪"Condition2", "BldgType",
                   "HouseStyle", "RoofStyle", "RoofMatl", "Exterior1st",␣
↪"Exterior2nd", "Alley",
```

```
                    "MasVnrType", "Foundation", "Heating", "CentralAir",␣
↪"Electrical", "Functional",
                    "GarageType", "PavedDrive", "SaleType", "SaleCondition",␣
↪"MiscFeature"]#, "Fence"]

len(cat_non_ordinal)
```

[23]: 29

[24]:
```
#DataFrame for later to check if code is right
hpp_non_ordinal = train_hpp[cat_non_ordinal]
```

[25]:
```
label_encoder = LabelEncoder()

#LabelEncoder for all non ordinal category columns
for col in cat_non_ordinal:
    train_hpp[col] = label_encoder.fit_transform(train_hpp[col])

#check
print(train_hpp.MSSubClass.value_counts())
print(hpp_non_ordinal.MSSubClass.value_counts())

print(train_hpp.MSZoning.value_counts())
print(hpp_non_ordinal.MSZoning.value_counts())

print(train_hpp.Street.value_counts())
print(hpp_non_ordinal.Street.value_counts())

print(train_hpp.LotShape.value_counts())
print(hpp_non_ordinal.LotShape.value_counts())
```

```
MSSubClass
0     536
5     299
4     144
11     87
1      69
12     63
6      60
8      57
10     52
14     30
9      20
7      16
3      12
13     10
2       4
Name: count, dtype: int64
```

```
MSSubClass
20     536
60     299
50     144
120     87
30      69
160     63
70      60
80      57
90      52
190     30
85      20
75      16
45      12
180     10
40       4
Name: count, dtype: int64
MSZoning
3    1150
4     218
1      65
2      16
0      10
Name: count, dtype: int64
MSZoning
RL         1150
RM          218
FV           65
RH           16
C (all)      10
Name: count, dtype: int64
Street
1    1453
0       6
Name: count, dtype: int64
Street
Pave    1453
Grvl       6
Name: count, dtype: int64
LotShape
3    924
0    484
1     41
2     10
Name: count, dtype: int64
LotShape
Reg    924
IR1    484
```

```
IR2     41
IR3     10
Name: count, dtype: int64
```

Encoding for categorical features with order

[26]:
```python
#ordinal columns
hpp_ordinal = train_hpp[["ExterQual", "ExterCond", "BsmtQual", "BsmtCond",
                        "BsmtExposure", "BsmtFinType1", "BsmtFinType2",␣
 ↪"HeatingQC",
                        "KitchenQual", "FireplaceQu", "GarageFinish",␣
 ↪"GarageQual",
                        "GarageCond", "PoolQC", "Fence"]]
```

[27]:
```python
##cat1
cat1 = ["Po", "Fa", "TA", "Gd", "Ex"]
enc1 = OrdinalEncoder(categories = [cat1])

ord_cat1 = ["ExterQual", "ExterCond", "HeatingQC", "KitchenQual"]

for col in ord_cat1:
    reshaped_data = train_hpp[col].values.reshape(-1, 1)
    train_hpp[col] = enc1.fit_transform(reshaped_data)

#check if it is right
print(hpp_ordinal[ord_cat1].apply(pd.value_counts))
print(train_hpp[ord_cat1].apply(pd.value_counts))
```

```
    ExterQual  ExterCond  HeatingQC  KitchenQual
Ex       52.0          3        741        100.0
Fa       14.0         28         49         39.0
Gd      488.0        146        240        585.0
Po        NaN          1          1          NaN
TA      905.0       1281        428        735.0
     ExterQual  ExterCond  HeatingQC  KitchenQual
0.0        NaN          1          1          NaN
1.0       14.0         28         49         39.0
2.0      905.0       1281        428        735.0
3.0      488.0        146        240        585.0
4.0       52.0          3        741        100.0
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2563003652.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2563003652.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat1].apply(pd.value_counts))
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2563003652.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2563003652.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2563003652.py:1
3: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(train_hpp[ord_cat1].apply(pd.value_counts))
```

[28]:

```
##cat2
cat2 = ["None", "Po", "Fa", "TA", "Gd", "Ex"]
enc2 = OrdinalEncoder(categories = [cat2])

ord_cat2 = ["BsmtQual", "BsmtCond", "FireplaceQu", "GarageQual", "GarageCond",␣
↪"PoolQC"]
            #"ExterQual", "ExterCond", "HeatingQC", "KitchenQual"]

for col in ord_cat2:
    reshaped_data = train_hpp[col].values.reshape(-1, 1)
    train_hpp[col] = enc2.fit_transform(reshaped_data)

#check if it is right
print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
print(train_hpp[ord_cat2].apply(pd.value_counts))
```

```
      BsmtQual  BsmtCond  FireplaceQu  GarageQual  GarageCond  PoolQC
Ex       121.0       NaN           24           3           2     2.0
Fa        35.0      45.0           33          48          35     2.0
Gd       617.0      65.0          380          14           9     3.0
None      37.0      37.0          689          81          81  1452.0
Po         NaN       2.0           20           3           7     NaN
TA       649.0    1310.0          313        1310        1325     NaN
     BsmtQual  BsmtCond  FireplaceQu  GarageQual  GarageCond  PoolQC
0.0      37.0      37.0          689          81          81  1452.0
1.0       NaN       2.0           20           3           7     NaN
2.0      35.0      45.0           33          48          35     2.0
3.0     649.0    1310.0          313        1310        1325     NaN
4.0     617.0      65.0          380          14           9     3.0
5.0     121.0       NaN           24           3           2     2.0
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\944483440.py:14
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(train_hpp[ord_cat2].apply(pd.value_counts))
```

[29]:

```
##cat3
cat3 = ["None", "Unf", "LwQ", "Rec", "BLQ", "ALQ", "GLQ"]
enc3 = OrdinalEncoder(categories = [cat3])

ord_cat3 = ["BsmtFinType1", "BsmtFinType2"]

for col in ord_cat3:
    reshaped_data = train_hpp[col].values.reshape(-1, 1)
    train_hpp[col] = enc3.fit_transform(reshaped_data)

#check if it is right
print(hpp_ordinal[ord_cat3].apply(pd.value_counts))
print(train_hpp[ord_cat3].apply(pd.value_counts))
```

```
      BsmtFinType1  BsmtFinType2
ALQ            220            19
BLQ            148            33
GLQ            418            14
LwQ             74            46
None            37            38
Rec            133            54
Unf            429          1255
     BsmtFinType1  BsmtFinType2
```

```
0.0             37            38
1.0            429          1255
2.0             74            46
3.0            133            54
4.0            148            33
5.0            220            19
6.0            418            14
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\1813528924.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat3].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\1813528924.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal[ord_cat3].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\1813528924.py:1
3: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(train_hpp[ord_cat3].apply(pd.value_counts))
```

[30]:

```
##cat4 BsmtExposure
cat4 = ["None", "No", "Mn", "Av", "Gd"]
enc4 = OrdinalEncoder(categories = [cat4])

train_hpp["BsmtExposure"] = enc4.fit_transform(train_hpp[["BsmtExposure"]])

#check if it is right
print(hpp_ordinal["BsmtExposure"].value_counts())
print(train_hpp["BsmtExposure"].value_counts())
```

```
BsmtExposure
No      952
Av      221
Gd      134
Mn      114
None     38
Name: count, dtype: int64
BsmtExposure
1.0    952
3.0    221
4.0    134
2.0    114
0.0     38
Name: count, dtype: int64
```

[31]:

```
##cat5 GarageFinish
cat5 = ["None", "Unf", "RFn", "Fin"]
```

```
enc5 = OrdinalEncoder(categories = [cat5])

train_hpp["GarageFinish"] = enc5.fit_transform(train_hpp[["GarageFinish"]])

#check if it is right
print(hpp_ordinal["GarageFinish"].value_counts())
print(train_hpp["GarageFinish"].value_counts())
```

```
GarageFinish
Unf     605
RFn     422
Fin     351
None     81
Name: count, dtype: int64
GarageFinish
1.0    605
2.0    422
3.0    351
0.0     81
Name: count, dtype: int64
```

[32]:
```
##cat6 GarageFinish
cat6 = ["None", "MnWw", "GdWo", "MnPrv", "GdPrv"]
enc6 = OrdinalEncoder(categories = [cat6])

train_hpp["Fence"] = enc6.fit_transform(train_hpp[["Fence"]])

#check if it is right
print(hpp_ordinal["Fence"].value_counts())
print(train_hpp["Fence"].value_counts())
```

```
Fence
None     1178
MnPrv     157
GdPrv      59
GdWo       54
MnWw       11
Name: count, dtype: int64
Fence
0.0    1178
3.0     157
4.0      59
2.0      54
1.0      11
Name: count, dtype: int64
```

[33]:
```
#see if all the features now have int or float data type
cat = train_hpp.select_dtypes(include = "O").keys()
```

```
cat
```

[33]: Index([], dtype='object')

1.2 Handle the test dataset

[35]:
```
test_df1 = pd.read_csv ("C:/Users/ZulkifliIndraGadingC/OneDrive/HTW/DL/Project/
↪test.csv")
test_df2 = pd.read_csv ("C:/Users/ZulkifliIndraGadingC/OneDrive/HTW/DL/Project/
↪sample_submission.csv")
```

[36]:
```
test_hpp = pd.merge(test_df1, test_df2, on = "Id")
test_hpp.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1459 entries, 0 to 1458
Data columns (total 81 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Id             1459 non-null   int64
 1   MSSubClass     1459 non-null   int64
 2   MSZoning       1455 non-null   object
 3   LotFrontage    1232 non-null   float64
 4   LotArea        1459 non-null   int64
 5   Street         1459 non-null   object
 6   Alley          107 non-null    object
 7   LotShape       1459 non-null   object
 8   LandContour    1459 non-null   object
 9   Utilities      1457 non-null   object
 10  LotConfig      1459 non-null   object
 11  LandSlope      1459 non-null   object
 12  Neighborhood   1459 non-null   object
 13  Condition1     1459 non-null   object
 14  Condition2     1459 non-null   object
 15  BldgType       1459 non-null   object
 16  HouseStyle     1459 non-null   object
 17  OverallQual    1459 non-null   int64
 18  OverallCond    1459 non-null   int64
 19  YearBuilt      1459 non-null   int64
 20  YearRemodAdd   1459 non-null   int64
 21  RoofStyle      1459 non-null   object
 22  RoofMatl       1459 non-null   object
 23  Exterior1st    1458 non-null   object
 24  Exterior2nd    1458 non-null   object
 25  MasVnrType     565 non-null    object
 26  MasVnrArea     1444 non-null   float64
 27  ExterQual      1459 non-null   object
 28  ExterCond      1459 non-null   object
```

```
29  Foundation     1459 non-null   object
30  BsmtQual       1415 non-null   object
31  BsmtCond       1414 non-null   object
32  BsmtExposure   1415 non-null   object
33  BsmtFinType1   1417 non-null   object
34  BsmtFinSF1     1458 non-null   float64
35  BsmtFinType2   1417 non-null   object
36  BsmtFinSF2     1458 non-null   float64
37  BsmtUnfSF      1458 non-null   float64
38  TotalBsmtSF    1458 non-null   float64
39  Heating        1459 non-null   object
40  HeatingQC      1459 non-null   object
41  CentralAir     1459 non-null   object
42  Electrical     1459 non-null   object
43  1stFlrSF       1459 non-null   int64
44  2ndFlrSF       1459 non-null   int64
45  LowQualFinSF   1459 non-null   int64
46  GrLivArea      1459 non-null   int64
47  BsmtFullBath   1457 non-null   float64
48  BsmtHalfBath   1457 non-null   float64
49  FullBath       1459 non-null   int64
50  HalfBath       1459 non-null   int64
51  BedroomAbvGr   1459 non-null   int64
52  KitchenAbvGr   1459 non-null   int64
53  KitchenQual    1458 non-null   object
54  TotRmsAbvGrd   1459 non-null   int64
55  Functional     1457 non-null   object
56  Fireplaces     1459 non-null   int64
57  FireplaceQu    729 non-null    object
58  GarageType     1383 non-null   object
59  GarageYrBlt    1381 non-null   float64
60  GarageFinish   1381 non-null   object
61  GarageCars     1458 non-null   float64
62  GarageArea     1458 non-null   float64
63  GarageQual     1381 non-null   object
64  GarageCond     1381 non-null   object
65  PavedDrive     1459 non-null   object
66  WoodDeckSF     1459 non-null   int64
67  OpenPorchSF    1459 non-null   int64
68  EnclosedPorch  1459 non-null   int64
69  3SsnPorch      1459 non-null   int64
70  ScreenPorch    1459 non-null   int64
71  PoolArea       1459 non-null   int64
72  PoolQC         3 non-null      object
73  Fence          290 non-null    object
74  MiscFeature    51 non-null     object
75  MiscVal        1459 non-null   int64
76  MoSold         1459 non-null   int64
```

```
 77  YrSold         1459 non-null   int64
 78  SaleType       1458 non-null   object
 79  SaleCondition  1459 non-null   object
 80  SalePrice      1459 non-null   float64
dtypes: float64(12), int64(26), object(43)
memory usage: 923.4+ KB
```

[37]:
```python
test_hpp.head()
```

[37]:
```
     Id  MSSubClass MSZoning  LotFrontage  LotArea Street Alley LotShape  \
0  1461          20       RH         80.0    11622   Pave   NaN      Reg
1  1462          20       RL         81.0    14267   Pave   NaN      IR1
2  1463          60       RL         74.0    13830   Pave   NaN      IR1
3  1464          60       RL         78.0     9978   Pave   NaN      IR1
4  1465         120       RL         43.0     5005   Pave   NaN      IR1

  LandContour Utilities  … PoolArea PoolQC  Fence MiscFeature MiscVal  \
0         Lvl    AllPub  …        0    NaN  MnPrv         NaN       0
1         Lvl    AllPub  …        0    NaN    NaN        Gar2   12500
2         Lvl    AllPub  …        0    NaN  MnPrv         NaN       0
3         Lvl    AllPub  …        0    NaN    NaN         NaN       0
4         HLS    AllPub  …        0    NaN    NaN         NaN       0

  MoSold YrSold  SaleType  SaleCondition      SalePrice
0      6   2010        WD         Normal  169277.052498
1      6   2010        WD         Normal  187758.393989
2      3   2010        WD         Normal  183583.683570
3      6   2010        WD         Normal  179317.477511
4      1   2010        WD         Normal  150730.079977

[5 rows x 81 columns]
```

[38]:
```python
#Drop column that have been dropped in train dataset
test_hpp = test_hpp.drop(columns = ["BsmtFinSF2", "LowQualFinSF",␣
 ↪"EnclosedPorch", "3SsnPorch",
                                    "ScreenPorch", "PoolArea", "MiscVal"])

#"PoolQC", "MiscFeature", "Alley", "Fence"
#Check Nan
test_hpp.isna().sum()[test_hpp.isna().sum() > 0].sort_values(ascending = False)
```

[38]:
```
PoolQC          1456
MiscFeature     1408
Alley           1352
Fence           1169
MasVnrType       894
FireplaceQu      730
LotFrontage      227
```

```
GarageCond        78
GarageYrBlt       78
GarageFinish      78
GarageQual        78
GarageType        76
BsmtCond          45
BsmtExposure      44
BsmtQual          44
BsmtFinType2      42
BsmtFinType1      42
MasVnrArea        15
MSZoning           4
BsmtFullBath       2
Functional         2
BsmtHalfBath       2
Utilities          2
KitchenQual        1
TotalBsmtSF        1
GarageCars         1
GarageArea         1
BsmtUnfSF          1
BsmtFinSF1         1
Exterior2nd        1
Exterior1st        1
SaleType           1
dtype: int64
```

[39]:

```
#Drop Na Value < 79
test_hpp.dropna(subset = ["GarageYrBlt"], inplace = True)
test_hpp.dropna(subset = ["BsmtCond"], inplace = True)
test_hpp.dropna(subset = ["MasVnrArea"], inplace = True)
test_hpp.dropna(subset = ["BsmtQual"], inplace = True)
test_hpp.dropna(subset = ["BsmtExposure"], inplace = True)
test_hpp.dropna(subset = ["MSZoning"], inplace = True)

droptest = ["Utilities", "KitchenQual", "Functional", "SaleType"]
test_hpp.dropna(subset = droptest, inplace = True)
```

[40]:

```
test_hpp.isna().sum()[test_hpp.isna().sum() > 0].sort_values(ascending = False)
```

[40]:

```
PoolQC         1317
MiscFeature    1276
Alley          1228
Fence          1051
MasVnrType      771
FireplaceQu     623
LotFrontage     211
```

```
dtype: int64
```

[41]:
```
# Impute the LotFrontage with median and the others two columns with None
test_hpp["LotFrontage"] = test_hpp["LotFrontage"].
 ↪fillna(test_hpp["LotFrontage"].median())

None_Val = ["PoolQC", "MiscFeature", "Alley", "Fence", "MasVnrType",␣
 ↪"FireplaceQu"]
test_hpp[None_Val] = test_hpp[None_Val].fillna(value = "None", inplace = False)

#check NA
test_hpp.isna().sum()[test_hpp.isna().sum() > 0].sort_values(ascending = False)
```

[41]:
```
Series([], dtype: int64)
```

1.2.1 Encoding test dataset

[42]:
```
## Encoding ##

cat_test = test_hpp.select_dtypes(include = "O").keys()
len(cat_test)
```

[42]:
```
43
```

[43]:
```
cat_non_ordinal = ["MSSubClass", "MSZoning", "Street", "LotShape",␣
 ↪"LandContour", "Utilities",
                    "LotConfig", "LandSlope","Neighborhood", "Condition1",␣
 ↪"Condition2", "BldgType",
                    "HouseStyle", "RoofStyle", "RoofMatl", "Exterior1st",␣
 ↪"Exterior2nd", "Alley",
                    "MasVnrType", "Foundation", "Heating", "CentralAir",␣
 ↪"Electrical", "Functional",
                    "GarageType", "PavedDrive", "SaleType", "SaleCondition",␣
 ↪"MiscFeature"]#, "Fence"]

len(cat_non_ordinal)
```

[43]:
```
29
```

[44]:
```
#later to check if code is right
hpp_non_ordinal_test = test_hpp[cat_non_ordinal]
```

[45]:
```
test_hpp[cat_non_ordinal].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1320 entries, 0 to 1458
Data columns (total 29 columns):
 #   Column         Non-Null Count  Dtype
```

```
---  ------         --------------  -----
 0   MSSubClass     1320 non-null   int64
 1   MSZoning       1320 non-null   object
 2   Street         1320 non-null   object
 3   LotShape       1320 non-null   object
 4   LandContour    1320 non-null   object
 5   Utilities      1320 non-null   object
 6   LotConfig      1320 non-null   object
 7   LandSlope      1320 non-null   object
 8   Neighborhood   1320 non-null   object
 9   Condition1     1320 non-null   object
 10  Condition2     1320 non-null   object
 11  BldgType       1320 non-null   object
 12  HouseStyle     1320 non-null   object
 13  RoofStyle      1320 non-null   object
 14  RoofMatl       1320 non-null   object
 15  Exterior1st    1320 non-null   object
 16  Exterior2nd    1320 non-null   object
 17  Alley          1320 non-null   object
 18  MasVnrType     1320 non-null   object
 19  Foundation     1320 non-null   object
 20  Heating        1320 non-null   object
 21  CentralAir     1320 non-null   object
 22  Electrical     1320 non-null   object
 23  Functional     1320 non-null   object
 24  GarageType     1320 non-null   object
 25  PavedDrive     1320 non-null   object
 26  SaleType       1320 non-null   object
 27  SaleCondition  1320 non-null   object
 28  MiscFeature    1320 non-null   object
dtypes: int64(1), object(28)
memory usage: 309.4+ KB
```

[46]:

```python
label_encoder = LabelEncoder()

#LabelEncoder for all non ordinal category columns
for col in cat_non_ordinal:
    test_hpp[col] = label_encoder.fit_transform(test_hpp[col])

#check
print(test_hpp.MSSubClass.value_counts())
print(hpp_non_ordinal_test.MSSubClass.value_counts())

print(test_hpp.MSZoning.value_counts())
print(hpp_non_ordinal_test.MSZoning.value_counts())

print(test_hpp.Street.value_counts())
```

```python
print(hpp_non_ordinal_test.Street.value_counts())

print(test_hpp.LotShape.value_counts())
print(hpp_non_ordinal_test.LotShape.value_counts())
```

```
MSSubClass
0     502
5     267
4     127
11     94
13     59
6      59
8      57
1      55
10     32
9      25
15     21
7       7
3       6
14      6
2       2
12      1
Name: count, dtype: int64
MSSubClass
20     502
60     267
50     127
120     94
160     59
70      59
80      57
30      55
90      32
85      25
190     21
75       7
45       6
180      6
40       2
150      1
Name: count, dtype: int64
MSZoning
3    1032
4     205
1      69
2       9
0       5
Name: count, dtype: int64
```

```
MSZoning
RL         1032
RM          205
FV           69
RH            9
C (all)       5
Name: count, dtype: int64
Street
1    1316
0       4
Name: count, dtype: int64
Street
Pave    1316
Grvl       4
Name: count, dtype: int64
LotShape
3    821
0    461
1     33
2      5
Name: count, dtype: int64
LotShape
Reg    821
IR1    461
IR2     33
IR3      5
Name: count, dtype: int64
```

[47]:
```
#ordinal columns
hpp_ordinal_test = test_hpp[["ExterQual", "ExterCond", "BsmtQual", "BsmtCond",
                        "BsmtExposure", "BsmtFinType1", "BsmtFinType2",␣
 ↪"HeatingQC",
                        "KitchenQual", "FireplaceQu", "GarageFinish",␣
 ↪"GarageQual",
                        "GarageCond", "PoolQC", "Fence"]]
```

[48]:
```
##cat1
cat1 = ["Po", "Fa", "TA", "Gd", "Ex"]
enc1 = OrdinalEncoder(categories = [cat1])

ord_cat1 = ["ExterQual", "ExterCond", "HeatingQC", "KitchenQual"]

for col in ord_cat1:
    reshaped_data = test_hpp[col].values.reshape(-1, 1)
    test_hpp[col] = enc1.fit_transform(reshaped_data)

#check if it is right
```

```
print(hpp_ordinal_test[ord_cat1].apply(pd.value_counts))
print(test_hpp[ord_cat1].apply(pd.value_counts))
```

```
    ExterQual  ExterCond  HeatingQC  KitchenQual
Ex       54.0          8        704         99.0
Fa        9.0         26         31         23.0
Gd      467.0        140        213        534.0
Po        NaN          1          1          NaN
TA      790.0       1145        371        664.0
     ExterQual  ExterCond  HeatingQC  KitchenQual
0.0        NaN          1          1          NaN
1.0        9.0         26         31         23.0
2.0      790.0       1145        371        664.0
3.0      467.0        140        213        534.0
4.0       54.0          8        704         99.0
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\4213809270.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\4213809270.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\4213809270.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\4213809270.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat1].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\4213809270.py:1
3: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(test_hpp[ord_cat1].apply(pd.value_counts))
```

[49]:
```
##cat2
cat2 = ["None", "Po", "Fa", "TA", "Gd", "Ex"]
enc2 = OrdinalEncoder(categories = [cat2])

ord_cat2 = ["BsmtQual", "BsmtCond", "FireplaceQu", "GarageQual", "GarageCond",␣
 ↪"PoolQC"]

for col in ord_cat2:
    reshaped_data = test_hpp[col].values.reshape(-1, 1)
    test_hpp[col] = enc2.fit_transform(reshaped_data)
```

```python
#check if it is right
print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
print(test_hpp[ord_cat2].apply(pd.value_counts))
```

```
      BsmtQual  BsmtCond  FireplaceQu  GarageQual  GarageCond  PoolQC
Ex       131.0       NaN           18         NaN         1.0     2.0
Fa        42.0      46.0           40        68.0        32.0     NaN
Gd       561.0      53.0          344        10.0         5.0     1.0
None       NaN       NaN          623         NaN         NaN  1317.0
Po         NaN       1.0           25         1.0         6.0     NaN
TA       586.0    1220.0          270      1241.0      1276.0     NaN
     BsmtQual  BsmtCond  FireplaceQu  GarageQual  GarageCond  PoolQC
0.0       NaN       NaN          623         NaN         NaN  1317.0
1.0       NaN       1.0           25         1.0         6.0     NaN
2.0      42.0      46.0           40        68.0        32.0     NaN
3.0     586.0    1220.0          270      1241.0      1276.0     NaN
4.0     561.0      53.0          344        10.0         5.0     1.0
5.0     131.0       NaN           18         NaN         1.0     2.0
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:12
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:12
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:12
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:12
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:12
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:12
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat2].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\107549150.py:13
: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(test_hpp[ord_cat2].apply(pd.value_counts))
```

[50]:
```
##cat3
cat3 = ["None", "Unf", "LwQ", "Rec", "BLQ", "ALQ", "GLQ"]
enc3 = OrdinalEncoder(categories = [cat3])

ord_cat3 = ["BsmtFinType1", "BsmtFinType2"]

for col in ord_cat3:
    reshaped_data = test_hpp[col].values.reshape(-1, 1)
    test_hpp[col] = enc3.fit_transform(reshaped_data)

#check if it is right
print(hpp_ordinal_test[ord_cat3].apply(pd.value_counts))
print(test_hpp[ord_cat3].apply(pd.value_counts))
```

```
     BsmtFinType1  BsmtFinType2
ALQ           201            32
BLQ           117            34
GLQ           414            20
LwQ            78            41
Rec           149            49
Unf           361          1144
     BsmtFinType1  BsmtFinType2
1.0           361          1144
2.0            78            41
3.0           149            49
4.0           117            34
5.0           201            32
6.0           414            20
```

```
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2921730565.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat3].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2921730565.py:1
2: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(hpp_ordinal_test[ord_cat3].apply(pd.value_counts))
C:\Users\ZulkifliIndraGadingC\AppData\Local\Temp\ipykernel_12248\2921730565.py:1
3: FutureWarning: pandas.value_counts is deprecated and will be removed in a
future version. Use pd.Series(obj).value_counts() instead.
  print(test_hpp[ord_cat3].apply(pd.value_counts))
```

[51]:
```
##cat4 BsmtExposure
cat4 = ["None", "No", "Mn", "Av", "Gd"]
enc4 = OrdinalEncoder(categories = [cat4])

test_hpp["BsmtExposure"] = enc4.fit_transform(test_hpp[["BsmtExposure"]])
```

```
#check if it is right
print(hpp_ordinal_test["BsmtExposure"].value_counts())
print(test_hpp["BsmtExposure"].value_counts())
```

```
BsmtExposure
No     880
Av     183
Gd     139
Mn     118
Name: count, dtype: int64
BsmtExposure
1.0    880
3.0    183
4.0    139
2.0    118
Name: count, dtype: int64
```

[52]:
```
##cat5 GarageFinish
cat5 = ["None", "Unf", "RFn", "Fin"]
enc5 = OrdinalEncoder(categories = [cat5])

test_hpp["GarageFinish"] = enc5.fit_transform(test_hpp[["GarageFinish"]])

#check if it is right
print(hpp_ordinal_test["GarageFinish"].value_counts())
print(test_hpp["GarageFinish"].value_counts())
```

```
GarageFinish
Unf    589
RFn    377
Fin    354
Name: count, dtype: int64
GarageFinish
1.0    589
2.0    377
3.0    354
Name: count, dtype: int64
```

[53]:
```
##cat6 Fence
cat6 = ["None", "MnWw", "GdWo", "MnPrv", "GdPrv"]
enc6 = OrdinalEncoder(categories = [cat6])

test_hpp["Fence"] = enc6.fit_transform(test_hpp[["Fence"]])

#check if it is right
print(hpp_ordinal_test["Fence"].value_counts())
print(test_hpp["Fence"].value_counts())
```

```
Fence
```

```
None     1051
MnPrv     161
GdPrv      55
GdWo       52
MnWw        1
Name: count, dtype: int64
Fence
0.0    1051
3.0     161
4.0      55
2.0      52
1.0       1
Name: count, dtype: int64
```

1.3 Neural Network Model

[55]:
```python
from sklearn.preprocessing import MinMaxScaler
from sklearn import linear_model
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from keras.models import Sequential
from keras import regularizers
from keras.layers import Dense
from keras.optimizers import Adam
```

```
WARNING:tensorflow:From C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-
packages\keras\src\losses.py:2976: The name
tf.losses.sparse_softmax_cross_entropy is deprecated. Please use
tf.compat.v1.losses.sparse_softmax_cross_entropy instead.
```

[56]:
```python
X_train = train_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)
#X_train = X_train.astype(float)
y_train = train_hpp['SalePrice']
#y_train = y_train.astype(float)
```

[57]:
```python
X_test = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)
#X_test = X_test.astype(float)
y_test = test_hpp["SalePrice"]
```

[58]:
```python
NN_model = Sequential()
NN_model.add(Dense(100, activation = "relu", input_dim = X_train.shape[1:][0]))
NN_model.add(Dense(50,activation = "relu"))
NN_model.add(Dense(1, activation = "linear"))
NN_model.compile(loss = "mse", optimizer = "adam")#, metrics = ['accuracy'])


history = NN_model.fit(X_train, y_train, epochs = 25)
```

```
WARNING:tensorflow:From C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-packages\keras\src\backend.py:873: The name tf.get_default_graph is deprecated. Please use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-packages\keras\src\optimizers\__init__.py:309: The name tf.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

Epoch 1/25
WARNING:tensorflow:From C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-packages\keras\src\utils\tf_utils.py:492: The name tf.ragged.RaggedTensorValue is deprecated. Please use tf.compat.v1.ragged.RaggedTensorValue instead.

46/46 [==============================] - 1s 2ms/step - loss: 34962604032.0000
Epoch 2/25
46/46 [==============================] - 0s 2ms/step - loss: 18937956352.0000
Epoch 3/25
46/46 [==============================] - 0s 2ms/step - loss: 4716284416.0000
Epoch 4/25
46/46 [==============================] - 0s 2ms/step - loss: 4045540864.0000
Epoch 5/25
46/46 [==============================] - 0s 3ms/step - loss: 3911441920.0000
Epoch 6/25
46/46 [==============================] - 0s 3ms/step - loss: 3761192960.0000
Epoch 7/25
46/46 [==============================] - 0s 3ms/step - loss: 3607258368.0000
Epoch 8/25
46/46 [==============================] - 0s 3ms/step - loss: 3423108096.0000
Epoch 9/25
46/46 [==============================] - 0s 2ms/step - loss: 3229111808.0000
Epoch 10/25
46/46 [==============================] - 0s 2ms/step - loss: 3011698944.0000
Epoch 11/25
46/46 [==============================] - 0s 2ms/step - loss: 2802041344.0000
Epoch 12/25
46/46 [==============================] - 0s 2ms/step - loss: 2579221248.0000
Epoch 13/25
46/46 [==============================] - 0s 2ms/step - loss: 2381913344.0000
Epoch 14/25
46/46 [==============================] - 0s 2ms/step - loss: 2199570432.0000
Epoch 15/25
46/46 [==============================] - 0s 2ms/step - loss: 2049209984.0000
Epoch 16/25
46/46 [==============================] - 0s 2ms/step - loss: 1965169920.0000
Epoch 17/25
46/46 [==============================] - 0s 2ms/step - loss: 1855754240.0000
Epoch 18/25
46/46 [==============================] - 0s 2ms/step - loss: 1804439552.0000
```

```
Epoch 19/25
46/46 [==============================] - 0s 2ms/step - loss: 1800855296.0000
Epoch 20/25
46/46 [==============================] - 0s 2ms/step - loss: 1767713152.0000
Epoch 21/25
46/46 [==============================] - 0s 2ms/step - loss: 1755873408.0000
Epoch 22/25
46/46 [==============================] - 0s 2ms/step - loss: 1706855680.0000
Epoch 23/25
46/46 [==============================] - 0s 3ms/step - loss: 1701621248.0000
Epoch 24/25
46/46 [==============================] - 0s 2ms/step - loss: 1679876224.0000
Epoch 25/25
46/46 [==============================] - 0s 2ms/step - loss: 1667862144.0000
```

[59]:
```python
predictions = NN_model.predict(X_test)
#print(predictions[:10])
#print(y_test[:10])
predicted_values_series = pd.Series(predictions.flatten(), name='Predicted␣
↪Values')
pred_actual = pd.concat([predicted_values_series, y_test], axis =  1)
pred_actual = pred_actual.dropna()
print(pred_actual)
```

```
42/42 [==============================] - 0s 2ms/step
      Predicted Values      SalePrice
0        134832.421875  169277.052498
1        199564.687500  187758.393989
2        194176.125000  183583.683570
3        194141.796875  179317.477511
4        160059.937500  150730.079977
…                  …            …
1315     156446.234375  182164.266854
1316      98026.742188  188137.901598
1317      96928.757812  158893.543063
1318     205859.500000  189579.650668
1319     237503.703125  165229.803506

[1199 rows x 2 columns]
```

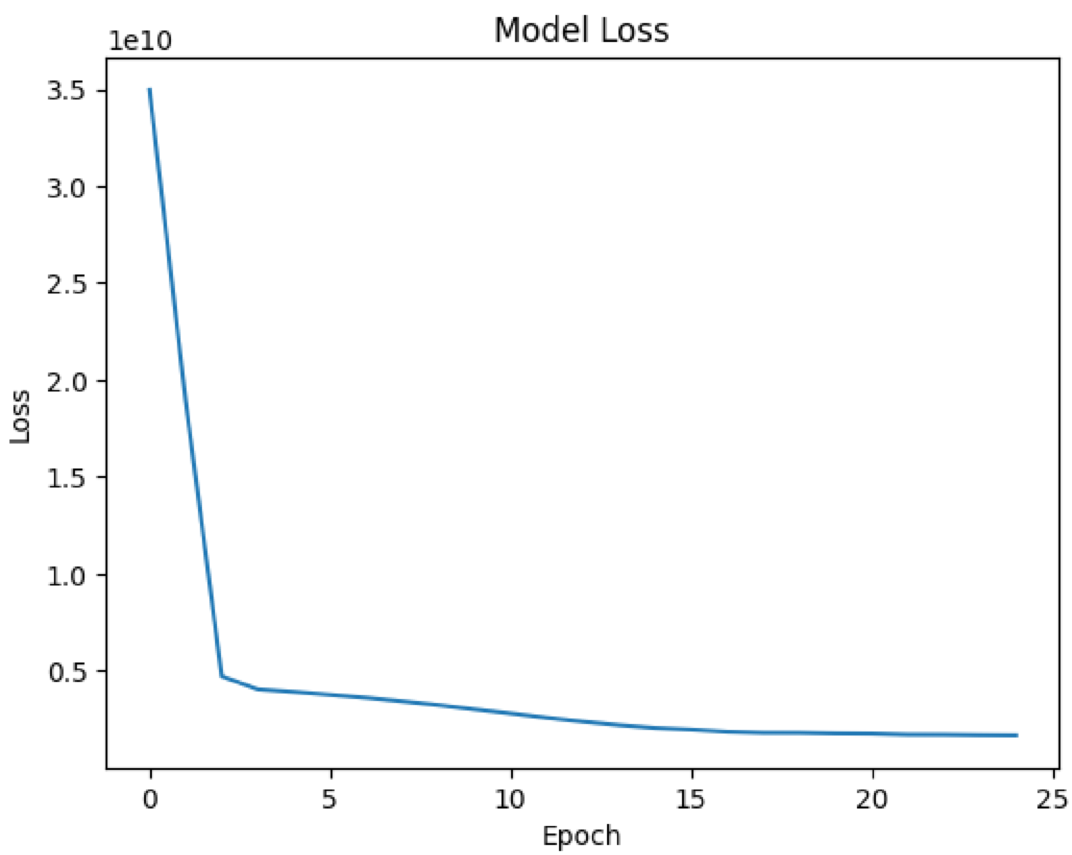
[60]:
```python
from sklearn.metrics import mean_squared_error, mean_absolute_error

y_pred = predictions

mse = mean_squared_error(y_test, y_pred)

rmse = np.sqrt(mse)
```

```
mae = mean_absolute_error(y_test, y_pred)

print("Mean Squared Error (MSE):", mse)
print("Root Mean Squared Error (RMSE):", rmse)
print("Mean Absolute Error (MAE):", mae)
```

```
Mean Squared Error (MSE): 4224925033.358688
Root Mean Squared Error (RMSE): 64999.42333097031
Mean Absolute Error (MAE): 47981.26673251824
```

1.3.1 The Loss Function

[63]:
```
plt.plot(history.history['loss'])
plt.title('Model Loss')
plt.xlabel('Epoch')
plt.ylabel('Loss')
plt.show()
```



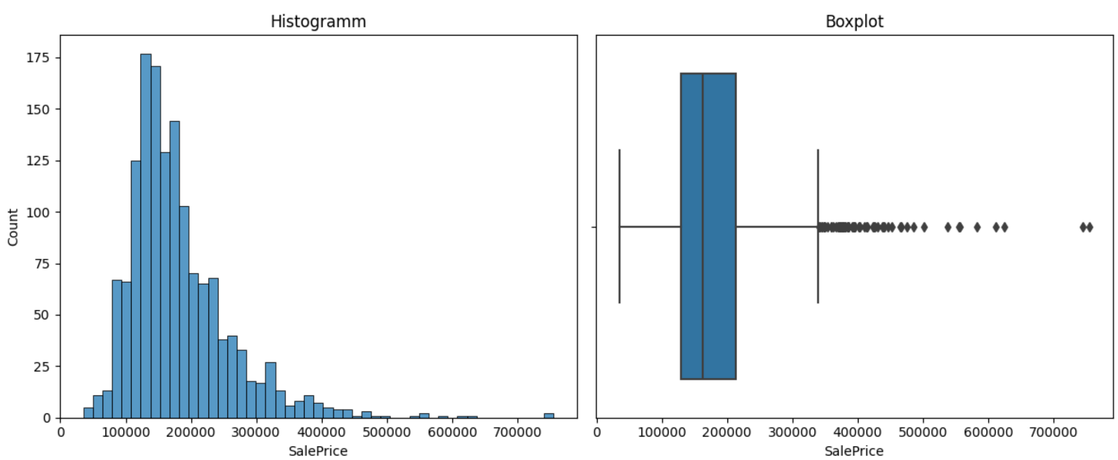
1.4 Delete outlier in SalePrice

Now we want to take a closer look in SalePrice and want to delete the outlier too.
Maybe it will lead to better results.

1.5 SP1 drop outlier in train_hpp.SalePrice and test_hpp.SalePrice stay

[64]:
```
fig, axes = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 5))

sns.histplot(x = train_hpp["SalePrice"], ax = axes[0])
axes[0].set_title("Histogramm")

sns.boxplot(x = train_hpp["SalePrice"], ax = axes[1])#, bins = 10, kde = True,␣
↪ax = axes[1])
axes[1].set_title("Boxplot")

# Menampilkan plot
plt.tight_layout()
plt.show()
```

```
C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-
packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



[65]:
```
train_hpp.SalePrice.describe()
```

[65]:
```
count      1459.000000
mean     180930.394791
std       79468.964025
min       34900.000000
```

```
25%       129950.000000
50%       163000.000000
75%       214000.000000
max       755000.000000
Name: SalePrice, dtype: float64
```

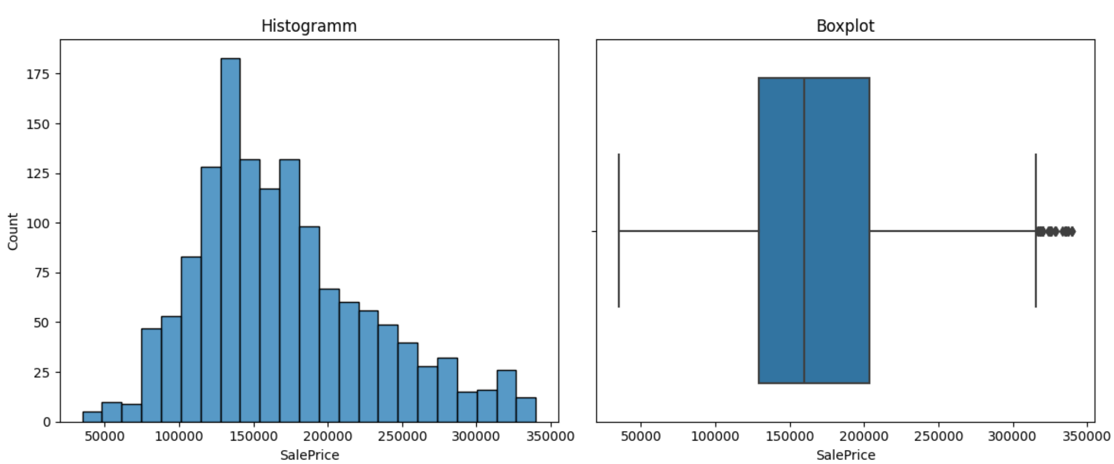
[66]:
```
Q1_SP1 = train_hpp["SalePrice"].quantile(0.25)
Q3_SP1 = train_hpp["SalePrice"].quantile(0.75)
IQR_SP1 = Q3_SP1 - Q1_SP1

upper_limit_SP1 = Q3_SP1 + 1.5 * IQR_SP1
print(upper_limit_SP1)
```

```
340075.0
```

[67]:
```
train_hpp_SP1 = train_hpp[train_hpp["SalePrice"] < upper_limit_SP1]
```

[68]:
```
fig, axes = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 5))

sns.histplot(x = train_hpp_SP1["SalePrice"], ax = axes[0])
axes[0].set_title("Histogramm")

sns.boxplot(x = train_hpp_SP1["SalePrice"], ax = axes[1])
axes[1].set_title("Boxplot")

# show plot
plt.tight_layout()
plt.show()
```

```
C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-
packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



[69]:
```
train_hpp_SP1.SalePrice.describe()
```

[69]:
```
count      1398.000000
mean     170239.085122
std       59251.280782
min       34900.000000
25%      129000.000000
50%      159500.000000
75%      203750.000000
max      340000.000000
Name: SalePrice, dtype: float64
```

[70]:
```
X_train_SP1 = train_hpp_SP1.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_SP1 = train_hpp_SP1['SalePrice']

X_test = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)
X_test = X_test.astype(float)
y_test = test_hpp["SalePrice"]
```

[71]:
```
NN_model_SP1 = Sequential()
NN_model_SP1.add(Dense(100, activation = "relu", input_dim = X_train_SP1.
 ↪shape[1:][0]))
NN_model_SP1.add(Dense(50,activation = "relu"))
NN_model_SP1.add(Dense(1, activation = "linear"))
NN_model_SP1.compile(loss = "mse", optimizer = "adam")#, metrics = ['accuracy'])


history_SP1 = NN_model_SP1.fit(X_train_SP1, y_train_SP1, epochs = 25)
```

```
Epoch 1/25
44/44 [==============================] - 1s 2ms/step - loss: 29805084672.0000
Epoch 2/25
44/44 [==============================] - 0s 2ms/step - loss: 19353792512.0000
Epoch 3/25
44/44 [==============================] - 0s 2ms/step - loss: 4583447040.0000
Epoch 4/25
44/44 [==============================] - 0s 2ms/step - loss: 2336613376.0000
Epoch 5/25
44/44 [==============================] - 0s 3ms/step - loss: 2252183296.0000
Epoch 6/25
44/44 [==============================] - 0s 3ms/step - loss: 2172681984.0000
Epoch 7/25
44/44 [==============================] - 0s 2ms/step - loss: 2097379328.0000
Epoch 8/25
```

```
44/44 [==============================] - 0s 2ms/step - loss: 2015254144.0000
Epoch 9/25
44/44 [==============================] - 0s 2ms/step - loss: 1931932800.0000
Epoch 10/25
44/44 [==============================] - 0s 3ms/step - loss: 1852883840.0000
Epoch 11/25
44/44 [==============================] - 0s 2ms/step - loss: 1768655744.0000
Epoch 12/25
44/44 [==============================] - 0s 2ms/step - loss: 1689832704.0000
Epoch 13/25
44/44 [==============================] - 0s 2ms/step - loss: 1619321600.0000
Epoch 14/25
44/44 [==============================] - 0s 2ms/step - loss: 1546730240.0000
Epoch 15/25
44/44 [==============================] - 0s 3ms/step - loss: 1471986688.0000
Epoch 16/25
44/44 [==============================] - 0s 3ms/step - loss: 1407796352.0000
Epoch 17/25
44/44 [==============================] - 0s 1ms/step - loss: 1349097728.0000
Epoch 18/25
44/44 [==============================] - 0s 2ms/step - loss: 1292273408.0000
Epoch 19/25
44/44 [==============================] - 0s 1ms/step - loss: 1242333696.0000
Epoch 20/25
44/44 [==============================] - 0s 1ms/step - loss: 1204641280.0000
Epoch 21/25
44/44 [==============================] - 0s 1ms/step - loss: 1164235648.0000
Epoch 22/25
44/44 [==============================] - 0s 1ms/step - loss: 1139057152.0000
Epoch 23/25
44/44 [==============================] - 0s 1ms/step - loss: 1105730944.0000
Epoch 24/25
44/44 [==============================] - 0s 2ms/step - loss: 1090346112.0000
Epoch 25/25
44/44 [==============================] - 0s 2ms/step - loss: 1071812672.0000
```

[72]:
```python
predictions_SP1 = NN_model_SP1.predict(X_test)

pred_actual_SP1 = pd.concat([predicted_values_series_SP1, y_test], axis =  1)
pred_actual_SP1 = pred_actual_SP1.dropna()
print(pred_actual_SP1)
```

```
42/42 [==============================] - 0s 2ms/step
      Predicted Values      SalePrice
0        145787.625000  169277.052498
1        197235.656250  187758.393989
2        195545.671875  183583.683570
3        194364.171875  179317.477511
```

```
4        164005.296875  150730.079977
…                  …              …
1315     165187.343750  182164.266854
1316     115710.304688  188137.901598
1317     115319.585938  158893.543063
1318     203919.203125  189579.650668
1319     224510.390625  165229.803506

[1199 rows x 2 columns]
```

[73]:
```python
y_pred_SP1 = predictions_SP1

mse_SP1 = mean_squared_error(y_test, y_pred_SP1)

rmse_SP1 = np.sqrt(mse_SP1)

mae_SP1 = mean_absolute_error(y_test, y_pred_SP1)

print("Mean Squared Error (MSE):", mse_SP1)
print("Root Mean Squared Error (RMSE):", rmse_SP1)
print("Mean Absolute Error (MAE):", mae_SP1)
```

```
Mean Squared Error (MSE): 2272148125.1893635
Root Mean Squared Error (RMSE): 47667.05492464752
Mean Absolute Error (MAE): 35670.623409943146
```

1.6 SP2 menghapus nilai SalePrice pada train_hpp yang lebih besar dari nilai maksimal dari SalePrice test_hpp

[74]:
```python
test_SP_max = test_hpp["SalePrice"].max()
print(test_SP_max)
```

```
277936.12694354
```

[75]:
```python
train_hpp_SP2 = train_hpp[train_hpp["SalePrice"] < test_SP_max]
train_hpp_SP2.SalePrice.describe()
```

[75]:
```
count      1312.000000
mean     161262.246951
std       49068.314794
min       34900.000000
25%      127000.000000
50%      155000.000000
75%      192000.000000
max      277500.000000
Name: SalePrice, dtype: float64
```

[76]:
```python
X_train_SP2 = train_hpp_SP2.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_SP2 = train_hpp_SP2['SalePrice']

X_test = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)
X_test = X_test.astype(float)
y_test = test_hpp["SalePrice"]
```

[77]:
```python
NN_model_SP2 = Sequential()
NN_model_SP2.add(Dense(100, activation = "relu", input_dim = X_train_SP2.
 ↪shape[1:][0]))
NN_model_SP2.add(Dense(50,activation = "relu"))
NN_model_SP2.add(Dense(1, activation = "linear"))
NN_model_SP2.compile(loss = "mse", optimizer = "adam")#, metrics = ['accuracy'])


history_SP2 = NN_model_SP2.fit(X_train_SP2, y_train_SP2, epochs = 25)
```

```
Epoch 1/25
41/41 [==============================] - 1s 2ms/step - loss: 26700394496.0000
Epoch 2/25
41/41 [==============================] - 0s 2ms/step - loss: 17306406912.0000
Epoch 3/25
41/41 [==============================] - 0s 2ms/step - loss: 3508643072.0000
Epoch 4/25
41/41 [==============================] - 0s 2ms/step - loss: 1667843200.0000
Epoch 5/25
41/41 [==============================] - 0s 2ms/step - loss: 1605766912.0000
Epoch 6/25
41/41 [==============================] - 0s 2ms/step - loss: 1546010368.0000
Epoch 7/25
41/41 [==============================] - 0s 2ms/step - loss: 1483359488.0000
Epoch 8/25
41/41 [==============================] - 0s 2ms/step - loss: 1418420864.0000
Epoch 9/25
41/41 [==============================] - 0s 2ms/step - loss: 1362541824.0000
Epoch 10/25
41/41 [==============================] - 0s 1ms/step - loss: 1308401536.0000
Epoch 11/25
41/41 [==============================] - 0s 2ms/step - loss: 1261163648.0000
Epoch 12/25
41/41 [==============================] - 0s 1ms/step - loss: 1208631936.0000
Epoch 13/25
41/41 [==============================] - 0s 2ms/step - loss: 1175427456.0000
Epoch 14/25
41/41 [==============================] - 0s 1ms/step - loss: 1134449920.0000
Epoch 15/25
41/41 [==============================] - 0s 1ms/step - loss: 1100378880.0000
```

```
Epoch 16/25
41/41 [==============================] - 0s 2ms/step - loss: 1072740992.0000
Epoch 17/25
41/41 [==============================] - 0s 2ms/step - loss: 1040289984.0000
Epoch 18/25
41/41 [==============================] - 0s 2ms/step - loss: 1017772352.0000
Epoch 19/25
41/41 [==============================] - 0s 2ms/step - loss: 985075008.0000
Epoch 20/25
41/41 [==============================] - 0s 2ms/step - loss: 965193344.0000
Epoch 21/25
41/41 [==============================] - 0s 2ms/step - loss: 941538048.0000
Epoch 22/25
41/41 [==============================] - 0s 2ms/step - loss: 921689088.0000
Epoch 23/25
41/41 [==============================] - 0s 2ms/step - loss: 909684352.0000
Epoch 24/25
41/41 [==============================] - 0s 3ms/step - loss: 891676800.0000
Epoch 25/25
41/41 [==============================] - 0s 3ms/step - loss: 885582144.0000
```

[78]:
```
predictions_SP2 = NN_model_SP2.predict(X_test)

predicted_values_series_SP2 = pd.Series(predictions_SP2.flatten(),␣
 ↪name='Predicted Values')
pred_actual_SP2 = pd.concat([predicted_values_series_SP2, y_test], axis =  1)
pred_actual_SP2 = pred_actual_SP2.dropna()
print(pred_actual_SP2)
```

```
42/42 [==============================] - 0s 1ms/step
      Predicted Values      SalePrice
0        143521.234375  169277.052498
1        184928.687500  187758.393989
2        186349.156250  183583.683570
3        185436.171875  179317.477511
4        159562.531250  150730.079977
…                  …              …
1315     157981.656250  182164.266854
1316     118675.085938  188137.901598
1317     118874.632812  158893.543063
1318     192336.796875  189579.650668
1319     210524.156250  165229.803506

[1199 rows x 2 columns]
```

[79]:
```
y_pred_SP2 = predictions_SP2

mse_SP2 = mean_squared_error(y_test, y_pred_SP2)
```

```
rmse_SP2 = np.sqrt(mse_SP2)

mae_SP2 = mean_absolute_error(y_test, y_pred_SP2)

print("Mean Squared Error (MSE):", mse_SP2)
print("Root Mean Squared Error (RMSE):", rmse_SP2)
print("Mean Absolute Error (MAE):", mae_SP2)
```

```
Mean Squared Error (MSE): 1517838637.6697886
Root Mean Squared Error (RMSE): 38959.44863149103
Mean Absolute Error (MAE): 30499.96627598869
```

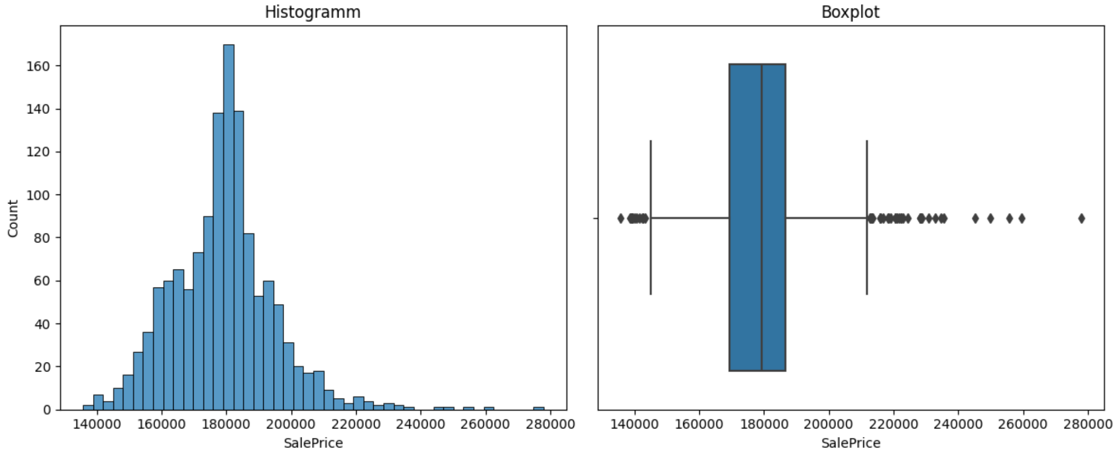
So far the best are SP2: delete the SalePrice in train_hpp that are bigger as the max SalePrice in test_hpp

1.7 SP3 clean outlier pada train dan test

[80]:
```
train_hpp_SP3 = train_hpp_SP1
```

[81]:
```
fig, axes = plt.subplots(nrows = 1, ncols = 2, figsize = (12, 5))

sns.histplot(x = test_hpp["SalePrice"], ax = axes[0])
axes[0].set_title("Histogramm")

sns.boxplot(x = test_hpp["SalePrice"], ax = axes[1])#, bins = 10, kde = True,␣
↪ax = axes[1])
axes[1].set_title("Boxplot")

# show plot
#sns.set_title("train SalePrice")
plt.tight_layout()
plt.show()
```

```
C:\Users\ZulkifliIndraGadingC\anaconda3\lib\site-
packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_na option is
deprecated and will be removed in a future version. Convert inf values to NaN
before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



[82]:
```
test_hpp.SalePrice.describe()
```

[82]:
```
count      1320.000000
mean     178984.247344
std       15818.201291
min      135751.318893
25%      169266.450745
50%      179288.048361
75%      186538.963233
max      277936.126944
Name: SalePrice, dtype: float64
```

[83]:
```
Q1_SP3_test = test_hpp["SalePrice"].quantile(0.25)
Q3_SP3_test = test_hpp["SalePrice"].quantile(0.75)
IQR_SP3_test = Q3_SP3_test - Q1_SP3_test

upper_limit_SP3_test = Q3_SP3_test + 1.5 * IQR_SP3_test
lower_limit_SP3_test = Q3_SP3_test - 1.5 * IQR_SP3_test
print(lower_limit_SP3_test)
print(upper_limit_SP3_test)
```

```
160630.19450040575
212447.73196497123
```

[84]:
```
test_hpp_SP3 = test_hpp[test_hpp["SalePrice"] < upper_limit_SP3_test]
test_hpp_SP3 = test_hpp[test_hpp["SalePrice"] > lower_limit_SP3_test]
test_hpp_SP3.SalePrice.describe()
```

[84]:
```
count      1158.000000
mean     182464.441654
std       13496.827641
min      160713.294603
```

```
25%      174388.867433
50%      180982.082617
75%      188189.186794
max      277936.126944
Name: SalePrice, dtype: float64
```

[85]:
```
X_train_SP3 = train_hpp_SP3.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_SP3 = train_hpp_SP3['SalePrice']

X_test_SP3 = test_hpp_SP3.drop(columns = ["Id", "SalePrice"], axis = 1)
X_test_SP3 = X_test_SP3.astype(float)
y_test_SP3 = test_hpp_SP3["SalePrice"]
```

[86]:
```
NN_model_SP3 = Sequential()
NN_model_SP3.add(Dense(100, activation = "relu", input_dim = X_train_SP3.
 ↪shape[1:][0]))
NN_model_SP3.add(Dense(50,activation = "relu"))
NN_model_SP3.add(Dense(1, activation = "linear"))
NN_model_SP3.compile(loss = "mse", optimizer = "adam")#, metrics = ['accuracy'])


history_SP3 = NN_model_SP3.fit(X_train_SP3, y_train_SP3, epochs = 25)
```

```
Epoch 1/25
44/44 [==============================] - 1s 2ms/step - loss: 29736284160.0000
Epoch 2/25
44/44 [==============================] - 0s 2ms/step - loss: 18133565440.0000
Epoch 3/25
44/44 [==============================] - 0s 2ms/step - loss: 3749156608.0000
Epoch 4/25
44/44 [==============================] - 0s 3ms/step - loss: 2374962432.0000
Epoch 5/25
44/44 [==============================] - 0s 3ms/step - loss: 2267625472.0000
Epoch 6/25
44/44 [==============================] - 0s 3ms/step - loss: 2197574656.0000
Epoch 7/25
44/44 [==============================] - 0s 2ms/step - loss: 2109751168.0000
Epoch 8/25
44/44 [==============================] - 0s 3ms/step - loss: 2021779840.0000
Epoch 9/25
44/44 [==============================] - 0s 3ms/step - loss: 1915647872.0000
Epoch 10/25
44/44 [==============================] - 0s 3ms/step - loss: 1825920384.0000
Epoch 11/25
44/44 [==============================] - 0s 2ms/step - loss: 1725437568.0000
Epoch 12/25
44/44 [==============================] - 0s 2ms/step - loss: 1620076032.0000
```

```
Epoch 13/25
44/44 [==============================] - 0s 2ms/step - loss: 1550901888.0000
Epoch 14/25
44/44 [==============================] - 0s 2ms/step - loss: 1450148864.0000
Epoch 15/25
44/44 [==============================] - 0s 2ms/step - loss: 1379200000.0000
Epoch 16/25
44/44 [==============================] - 0s 2ms/step - loss: 1314407808.0000
Epoch 17/25
44/44 [==============================] - 0s 2ms/step - loss: 1233915520.0000
Epoch 18/25
44/44 [==============================] - 0s 2ms/step - loss: 1174739200.0000
Epoch 19/25
44/44 [==============================] - 0s 2ms/step - loss: 1140230272.0000
Epoch 20/25
44/44 [==============================] - 0s 2ms/step - loss: 1106826112.0000
Epoch 21/25
44/44 [==============================] - 0s 3ms/step - loss: 1078652800.0000
Epoch 22/25
44/44 [==============================] - 0s 3ms/step - loss: 1055413376.0000
Epoch 23/25
44/44 [==============================] - 0s 3ms/step - loss: 1041840576.0000
Epoch 24/25
44/44 [==============================] - 0s 3ms/step - loss: 1041377920.0000
Epoch 25/25
44/44 [==============================] - 0s 3ms/step - loss: 1028853120.0000
```

[87]:
```
predictions_SP3 = NN_model_SP3.predict(X_test_SP3)

predicted_values_series_SP3 = pd.Series(predictions_SP3.flatten(),␣
↪name='Predicted Values')
pred_actual_SP3 = pd.concat([predicted_values_series_SP3, y_test_SP3], axis = ␣
↪1)
pred_actual_SP3 = pred_actual_SP3.dropna()
print(pred_actual_SP3)
```

```
37/37 [==============================] - 0s 2ms/step
      Predicted Values      SalePrice
0        136431.156250  169277.052498
1        187621.109375  187758.393989
2        186479.718750  183583.683570
3        186769.984375  179317.477511
5        172939.078125  177150.989247
…                  …              …
1153     152817.359375  189562.873697
1154     107487.406250  170591.884966
1155     106813.203125  172934.351683
1156     194646.343750  186425.069879
```

```
1157     219026.500000  218648.131133

[911 rows x 2 columns]
```

[88]:
```
y_pred_SP3 = predictions_SP3

mse_SP3 = mean_squared_error(y_test_SP3, y_pred_SP3)

rmse_SP3 = np.sqrt(mse_SP3)

mae_SP3 = mean_absolute_error(y_test_SP3, y_pred_SP3)

print("Mean Squared Error (MSE):", mse_SP3)
print("Root Mean Squared Error (RMSE):", rmse_SP3)
print("Mean Absolute Error (MAE):", mae_SP3)
```

```
Mean Squared Error (MSE): 2468234292.346705
Root Mean Squared Error (RMSE): 49681.32740121488
Mean Absolute Error (MAE): 38675.832682657005
```

1.7.1 So far our best MAE and RMSE are from SP0

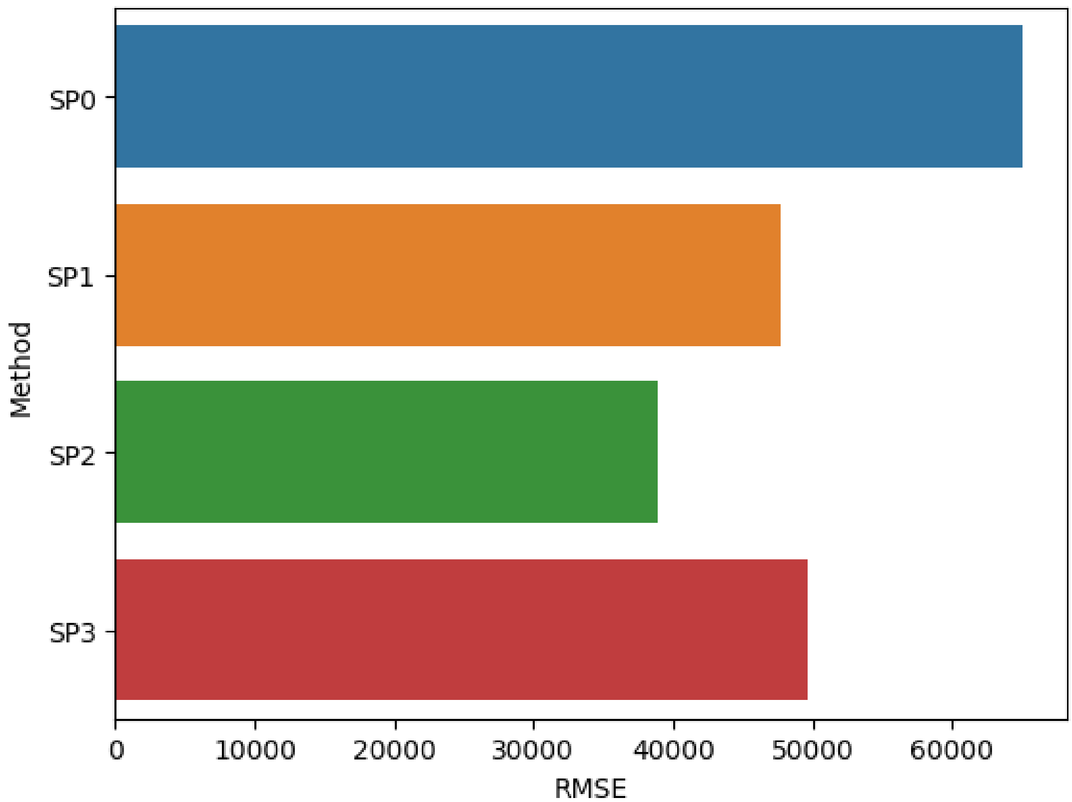
[89]:
```
#Summary of MAE and RMSE
error_summary = {'Method': ["SP0", "SP1", "SP2", "SP3"],
                 'RMSE': [rmse, rmse_SP1, rmse_SP2, rmse_SP3],
                 'MAE': [mae, mae_SP1, mae_SP2, mae_SP3]}
error_summary = pd.DataFrame(error_summary)
error_summary
```

[89]:

	Method	RMSE	MAE
0	SP0	64999.423331	47981.266733
1	SP1	47667.054925	35670.623410
2	SP2	38959.448631	30499.966276
3	SP3	49681.327401	38675.832683

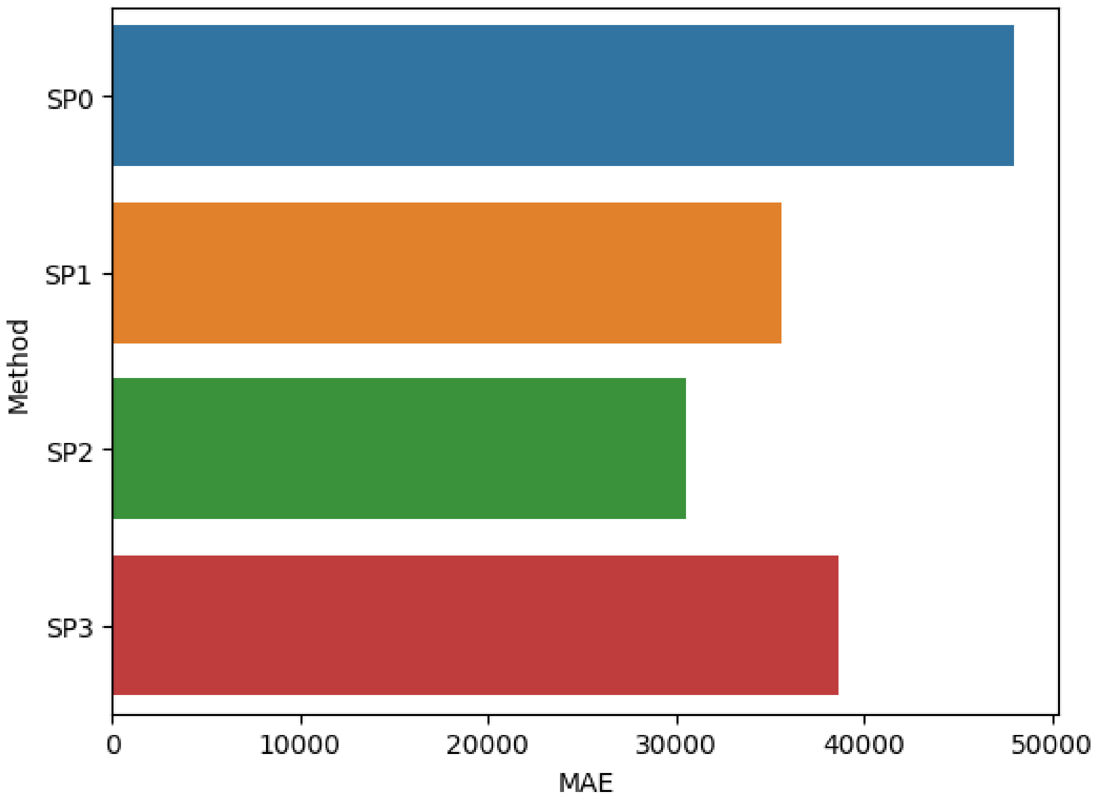
[90]:
```
sns.barplot(data = error_summary, y = "Method", x = "RMSE")
```

[90]: <Axes: xlabel='RMSE', ylabel='Method'>



[91]:
```
sns.barplot(data = error_summary, y = "Method", x = "MAE")
```

[91]: <Axes: xlabel='MAE', ylabel='Method'>



1.8 Train Test Split

1.8.1 Train Split

[92]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.metrics import accuracy_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.utils import to_categorical
```

[115]:
```
X = train_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y = train_hpp['SalePrice']
```

[116]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

[117]:
```
NN_model_split = Sequential()
NN_model_split.add(Dense(100, activation = "relu", input_dim = X_train.shape[1:
 ↪][0]))
NN_model_split.add(Dense(50,activation = "relu"))
```

```
NN_model_split.add(Dense(1, activation = "linear"))
NN_model_split.compile(loss = "mse", optimizer = "adam")#, metrics =␣
 ↪['accuracy'])


history_split = NN_model_split.fit(X_train, y_train, epochs = 25)
```

```
Epoch 1/25
37/37 [==============================] - 1s 2ms/step - loss: 37514035200.0000
Epoch 2/25
37/37 [==============================] - 0s 2ms/step - loss: 29102757888.0000
Epoch 3/25
37/37 [==============================] - 0s 2ms/step - loss: 10535622656.0000
Epoch 4/25
37/37 [==============================] - 0s 2ms/step - loss: 4153363712.0000
Epoch 5/25
37/37 [==============================] - 0s 2ms/step - loss: 3995614464.0000
Epoch 6/25
37/37 [==============================] - 0s 2ms/step - loss: 3884705792.0000
Epoch 7/25
37/37 [==============================] - 0s 2ms/step - loss: 3770810880.0000
Epoch 8/25
37/37 [==============================] - 0s 2ms/step - loss: 3666938880.0000
Epoch 9/25
37/37 [==============================] - 0s 2ms/step - loss: 3514869504.0000
Epoch 10/25
37/37 [==============================] - 0s 2ms/step - loss: 3375560704.0000
Epoch 11/25
37/37 [==============================] - 0s 2ms/step - loss: 3224022016.0000
Epoch 12/25
37/37 [==============================] - 0s 2ms/step - loss: 3089069824.0000
Epoch 13/25
37/37 [==============================] - 0s 1ms/step - loss: 2873638912.0000
Epoch 14/25
37/37 [==============================] - 0s 2ms/step - loss: 2702150656.0000
Epoch 15/25
37/37 [==============================] - 0s 1ms/step - loss: 2518575104.0000
Epoch 16/25
37/37 [==============================] - 0s 1ms/step - loss: 2353385728.0000
Epoch 17/25
37/37 [==============================] - 0s 1ms/step - loss: 2187945216.0000
Epoch 18/25
37/37 [==============================] - 0s 1ms/step - loss: 2075086592.0000
Epoch 19/25
37/37 [==============================] - 0s 2ms/step - loss: 1983096960.0000
Epoch 20/25
37/37 [==============================] - 0s 2ms/step - loss: 1921186432.0000
Epoch 21/25
```

```
37/37 [==============================] - 0s 2ms/step - loss: 1879758336.0000
Epoch 22/25
37/37 [==============================] - 0s 2ms/step - loss: 1829169280.0000
Epoch 23/25
37/37 [==============================] - 0s 2ms/step - loss: 1828028416.0000
Epoch 24/25
37/37 [==============================] - 0s 2ms/step - loss: 1795054208.0000
Epoch 25/25
37/37 [==============================] - 0s 2ms/step - loss: 1786922112.0000
```

[118]:

```
#train SP1
predictions_train_split = NN_model_split.predict(X_test)

predicted_values_series_train_split = pd.Series(predictions_train_split.
 ↪flatten(), name = 'Predicted Values')
pred_actual_train_split = pd.concat([predicted_values_series_train_split,␣
 ↪y_test], axis =  1)
pred_actual_train_split = pred_actual_train_split.dropna()
print(pred_actual_train_split)
```

```
10/10 [==============================] - 0s 2ms/step
     Predicted Values  SalePrice
0       197442.671875   208500.0
3       110634.578125   140000.0
5       283892.437500   143000.0
7       292520.750000   200000.0
19      314212.937500   139000.0
..                ...        ...
251     165933.765625   235000.0
270     161757.312500   266000.0
271     201154.500000   241500.0
284     173576.500000   179200.0
291     242587.296875   135900.0

[66 rows x 2 columns]
```

[119]:

```
#train SP1
y_pred_train = predictions_train_split

mse_train = mean_squared_error(y_test, y_pred_train)

rmse_train = np.sqrt(mse_train)

mae_train = mean_absolute_error(y_test, y_pred_train)

print("Mean Squared Error (MSE):", mse_train)
print("Root Mean Squared Error (RMSE):", rmse_train)
print("Mean Absolute Error (MAE):", mae_train)
```

```
Mean Squared Error (MSE): 1433373365.412218
Root Mean Squared Error (RMSE): 37859.917662512395
Mean Absolute Error (MAE): 28121.727579195205
```

Test Split SP0

[125]:
```
X_tr = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y_tr = test_hpp["SalePrice"]
```

[126]:
```
X_train, X_test, y_train, y_test = train_test_split(X_tr, y_tr, test_size=0.2)
```

[127]:
```
NN_model_split_ts = Sequential()
NN_model_split_ts.add(Dense(100, activation = "relu", input_dim = X_train.
 ↪shape[1:][0]))
NN_model_split_ts.add(Dense(50,activation = "relu"))
NN_model_split_ts.add(Dense(1, activation = "linear"))
NN_model_split_ts.compile(loss = "mse", optimizer = "adam")#, metrics =␣
 ↪['accuracy'])


history_split_ts = NN_model_split_ts.fit(X_train, y_train, epochs = 25)
```

```
Epoch 1/25
33/33 [==============================] - 1s 2ms/step - loss: 29457991680.0000
Epoch 2/25
33/33 [==============================] - 0s 1ms/step - loss: 20542031872.0000
Epoch 3/25
33/33 [==============================] - 0s 1ms/step - loss: 6187458048.0000
Epoch 4/25
33/33 [==============================] - 0s 2ms/step - loss: 1268209920.0000
Epoch 5/25
33/33 [==============================] - 0s 1ms/step - loss: 1141002880.0000
Epoch 6/25
33/33 [==============================] - 0s 1ms/step - loss: 1015928960.0000
Epoch 7/25
33/33 [==============================] - 0s 1ms/step - loss: 919784768.0000
Epoch 8/25
33/33 [==============================] - 0s 1ms/step - loss: 804408000.0000
Epoch 9/25
33/33 [==============================] - 0s 1ms/step - loss: 705597376.0000
Epoch 10/25
33/33 [==============================] - 0s 1ms/step - loss: 605570688.0000
Epoch 11/25
33/33 [==============================] - 0s 1ms/step - loss: 514492640.0000
Epoch 12/25
33/33 [==============================] - 0s 1ms/step - loss: 439146112.0000
Epoch 13/25
33/33 [==============================] - 0s 1ms/step - loss: 366392352.0000
```

```
Epoch 14/25
33/33 [==============================] - 0s 1ms/step - loss: 311962400.0000
Epoch 15/25
33/33 [==============================] - 0s 1ms/step - loss: 259648432.0000
Epoch 16/25
33/33 [==============================] - 0s 1ms/step - loss: 221485872.0000
Epoch 17/25
33/33 [==============================] - 0s 1ms/step - loss: 192455584.0000
Epoch 18/25
33/33 [==============================] - 0s 1ms/step - loss: 170887488.0000
Epoch 19/25
33/33 [==============================] - 0s 1ms/step - loss: 156104864.0000
Epoch 20/25
33/33 [==============================] - 0s 1ms/step - loss: 141545168.0000
Epoch 21/25
33/33 [==============================] - 0s 1ms/step - loss: 133851264.0000
Epoch 22/25
33/33 [==============================] - 0s 1ms/step - loss: 125844208.0000
Epoch 23/25
33/33 [==============================] - 0s 1ms/step - loss: 120315008.0000
Epoch 24/25
33/33 [==============================] - 0s 2ms/step - loss: 115114056.0000
Epoch 25/25
33/33 [==============================] - 0s 2ms/step - loss: 111178920.0000
```

[128]:

```
#train SP1
predictions_test_split = NN_model_split_ts.predict(X_test)

predicted_values_series_test_split = pd.Series(predictions_test_split.
 ↪flatten(), name = 'Predicted Values')
pred_actual_test_split = pd.concat([predicted_values_series_test_split,␣
 ↪y_test], axis =  1)
pred_actual_test_split = pred_actual_test_split.dropna()
print(pred_actual_test_split)
```

```
9/9 [==============================] - 0s 1ms/step
     Predicted Values      SalePrice
1       173476.406250  187758.393989
9       168268.187500  160726.247831
15      169529.562500  179460.965187
17      161813.500000  182352.192645
22      195002.187500  190552.829321
35      172573.078125  152605.298564
51      198097.421875  176521.216976
52      187441.953125  179436.704810
61      172495.656250  179423.751582
64      188841.937500  181122.168677
66      199798.468750  159738.292580
```

```
68       159032.421875  174706.363660
70       166355.421875  163602.512173
74       165585.250000  183003.613338
90       173035.265625  155134.227843
104      178140.906250  191736.759806
107      192853.203125  205469.409445
109      187979.546875  182271.503072
129      221308.359375  172088.872656
141      165666.031250  162182.596210
148      180926.156250  160172.727974
150      178733.093750  176515.497545
158      179475.156250  169556.835902
168      173131.515625  177109.589956
174      161563.218750  179007.601964
175      177739.000000  180370.808623
176      168312.234375  185102.616731
177      174017.343750  198825.563452
184      186127.156250  179024.491270
186      178586.750000  184534.676688
193      158873.406250  168434.977996
195      156314.703125  164096.097354
201      176234.625000  185988.233988
204      166451.296875  184468.908382
208      190968.828125  164279.130482
211      194063.390625  191742.778119
216      179559.265625  166481.866476
217      169061.984375  172080.434497
220      163002.218750  157829.546855
225      180033.812500  155774.270902
227      176567.343750  179605.563664
232      154663.125000  178630.060560
234      178791.218750  172515.687369
235      178614.312500  204032.992923
244      178762.906250  181878.647957
253      212506.656250  179980.635949
260      209818.937500  185199.372568
262      166423.343750  185080.145269
```

[129]:

```
#test SPO
y_pred_test = predictions_test_split

mse_test = mean_squared_error(y_test, y_pred_test)

rmse_test = np.sqrt(mse_test)

mae_test = mean_absolute_error(y_test, y_pred_test)
```

```python
print("Mean Squared Error (MSE):", mse_test)
print("Root Mean Squared Error (RMSE):", rmse_test)
print("Mean Absolute Error (MAE):", mae_test)
```

```
Mean Squared Error (MSE): 116151087.99454619
Root Mean Squared Error (RMSE): 10777.341415884819
Mean Absolute Error (MAE): 8340.645129613655
```

1.9 Compare the best RF Regressor

Compare with RF Regressor SP0

[130]:
```python
X_train_RF = train_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_RF = train_hpp['SalePrice']

X_test_RF = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y_test_RF = test_hpp["SalePrice"]
```

[138]:
```python
from sklearn.ensemble import RandomForestRegressor

# Inisialization model Random Forest Regressor
rf_regressor = RandomForestRegressor(n_estimators=50)
# fit the RF model
rf_regressor.fit(X_train_RF, y_train_RF)
```

[138]:
```
RandomForestRegressor(n_estimators=50)
```

[139]:
```python
#predict
y_pred_RF = rf_regressor.predict(X_test_RF)

# Evaluate the model
mse_RF = mean_squared_error(y_test_RF, y_pred_RF)
rmse_RF = np.sqrt(mse_RF)
mae_RF = mean_absolute_error(y_test_RF, y_pred_RF)

# Show result evaluation
print(f'Mean Squared Error (MSE): {mse_RF:.2f}')
print(f'Mean Squared Error (RMSE): {rmse_RF:.2f}')
print(f'Mean Absolute Error (MAE): {mae_RF:.2f}')
```

```
Mean Squared Error (MSE): 4813494539.26
Mean Squared Error (RMSE): 69379.35
Mean Absolute Error (MAE): 52194.73
```

[121]:
```python
features_RF = list(X_train_RF.columns)
importances_RF = rf_regressor.feature_importances_
indices_RF = np.argsort(importances_RF)
```

```
plt.figure(figsize=(8,30))
plt.title('Feature Importances')
plt.barh(range(len(indices_RF)), importances_RF[indices_RF], color='b',␣
 ↪align='center')
plt.yticks(range(len(indices_RF)), [features_RF[i] for i in indices_RF])
plt.xlabel('Relative Importance')
plt.tick_params(axis='both', which='major', labelsize=6)
plt.show()
```


Feature Importances
OverallQual
GrLivArea
TotalBsmtSF
2ndFlrSF
BsmtFinSF1
GarageCars
1stFlrSF
GarageArea
LotArea
TotRmsAbvGrd
Neighborhood
BsmtQual
YearBuilt
KitchenQual
YearRemodAdd
FireplaceQu
LotFrontage
GarageYrBlt
WoodDeckSF
OpenPorchSF
BsmtUnfSF
OverallCond
MoSold
FullBath
GarageFinish
LandContour
GarageType
BsmtExposure
CentralAir
ExterQual
MasVnrArea
BsmtFinType1
Exterior1st
BedroomAbvGr
Fireplaces
MSZoning
MSSubClass
SaleCondition
Exterior2nd
YrSold
MasVnrType
LotShape
HalfBath
BsmtFinType2
KitchenAbvGr
RoofStyle
BsmtFullBath
LotConfig
HeatingQC
HouseStyle
SaleType
Functional
LandSlope
BsmtCond
GarageQual
ExterCond
Condition1
PavedDrive
PoolQC
GarageCond
Foundation
Fence
BsmtHalfBath
RoofMatl
Alley
BldgType
Electrical
Condition2
Heating
MiscFeature
Street
Utilities
0.0
0.1
0.2
0.3
0.4
0.5
Relative Importance

Compare with RF SP1

[140]:
```
X_train_RF_SP1 = train_hpp_SP1.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_RF_SP1 = train_hpp_SP1['SalePrice']

X_test_RF_SP1 = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y_test_RF_SP1 = test_hpp["SalePrice"]
```

[141]:
```
rf_regressor_SP1 = RandomForestRegressor(n_estimators=50)

rf_regressor_SP1.fit(X_train_RF_SP1, y_train_RF_SP1)
```

[141]:
```
RandomForestRegressor(n_estimators=50)
```

[142]:
```
y_pred_RF_SP1 = rf_regressor_SP1.predict(X_test_RF_SP1)

mse_RF_SP1 = mean_squared_error(y_test_RF_SP1, y_pred_RF_SP1)
rmse_RF_SP1 = np.sqrt(mse_RF_SP1)
mae_RF_SP1 = mean_absolute_error(y_test_RF_SP1, y_pred_RF_SP1)

print(f'Mean Squared Error (MSE): {mse_RF_SP1:.2f}')
print(f'Mean Squared Error (RMSE): {rmse_RF_SP1:.2f}')
print(f'Mean Absolute Error (MAE): {mae_RF_SP1:.2f}')
```

```
Mean Squared Error (MSE): 3049457492.58
Mean Squared Error (RMSE): 55221.89
Mean Absolute Error (MAE): 46245.42
```

Compare with RF SP2

[143]:
```
X_train_RF_SP2 = train_hpp_SP2.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_RF_SP2 = train_hpp_SP2['SalePrice']

X_test_RF_SP2 = test_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y_test_RF_SP2 = test_hpp["SalePrice"]
```

[144]:
```
# Inisialization model Random Forest Regressor
rf_regressor_SP2 = RandomForestRegressor(n_estimators=50)
# fit the RF model
rf_regressor_SP2.fit(X_train_RF_SP2, y_train_RF_SP2)
```

[144]:
```
RandomForestRegressor(n_estimators=50)
```

[145]:
```python
# predict
y_pred_RF_SP2 = rf_regressor_SP2.predict(X_test_RF_SP2)

# Evaluate the model
mse_RF_SP2 = mean_squared_error(y_test_RF_SP2, y_pred_RF_SP2)
rmse_RF_SP2 = np.sqrt(mse_RF_SP2)
mae_RF_SP2 = mean_absolute_error(y_test_RF_SP2, y_pred_RF_SP2)

# Show the result evaluate
print(f'Mean Squared Error (MSE): {mse_RF_SP2:.2f}')
print(f'Mean Squared Error (RMSE): {rmse_RF_SP2:.2f}')
print(f'Mean Absolute Error (MAE): {mae_RF_SP2:.2f}')
```

```
Mean Squared Error (MSE): 2082168334.13
Mean Squared Error (RMSE): 45630.78
Mean Absolute Error (MAE): 39828.79
```

Compare with RF SP3

[149]:
```python
X_train_RF_SP3 = train_hpp_SP3.drop(columns = ["Id", "SalePrice"], axis = 1)

y_train_RF_SP3 = train_hpp_SP3['SalePrice']

X_test_RF_SP3 = test_hpp_SP3.drop(columns = ["Id", "SalePrice"], axis = 1)

y_test_RF_SP3 = test_hpp_SP3["SalePrice"]
```

[150]:
```python
# Inisialization model Random Forest Regressor
rf_regressor_SP3 = RandomForestRegressor(n_estimators=50)
# Fit the model
rf_regressor_SP3.fit(X_train_RF_SP3, y_train_RF_SP3)
```

[150]:
```
RandomForestRegressor(n_estimators=50)
```

[151]:
```python
# Predict
y_pred_RF_SP3 = rf_regressor_SP3.predict(X_test_RF_SP3)

# Evaluate the model
mse_RF_SP3 = mean_squared_error(y_test_RF_SP3, y_pred_RF_SP3)
rmse_RF_SP3 = np.sqrt(mse_RF_SP3)
mae_RF_SP3 = mean_absolute_error(y_test_RF_SP3, y_pred_RF_SP3)

# Show the model evaluate
print(f'Mean Squared Error (MSE): {mse_RF_SP3:.2f}')
print(f'Mean Squared Error (RMSE): {rmse_RF_SP3:.2f}')
print(f'Mean Absolute Error (MAE): {mae_RF_SP3:.2f}')
```

```
Mean Squared Error (MSE): 3063641777.44
Mean Squared Error (RMSE): 55350.17
```

```
Mean Absolute Error (MAE): 46111.43
```

1.9.1 Summary of RF

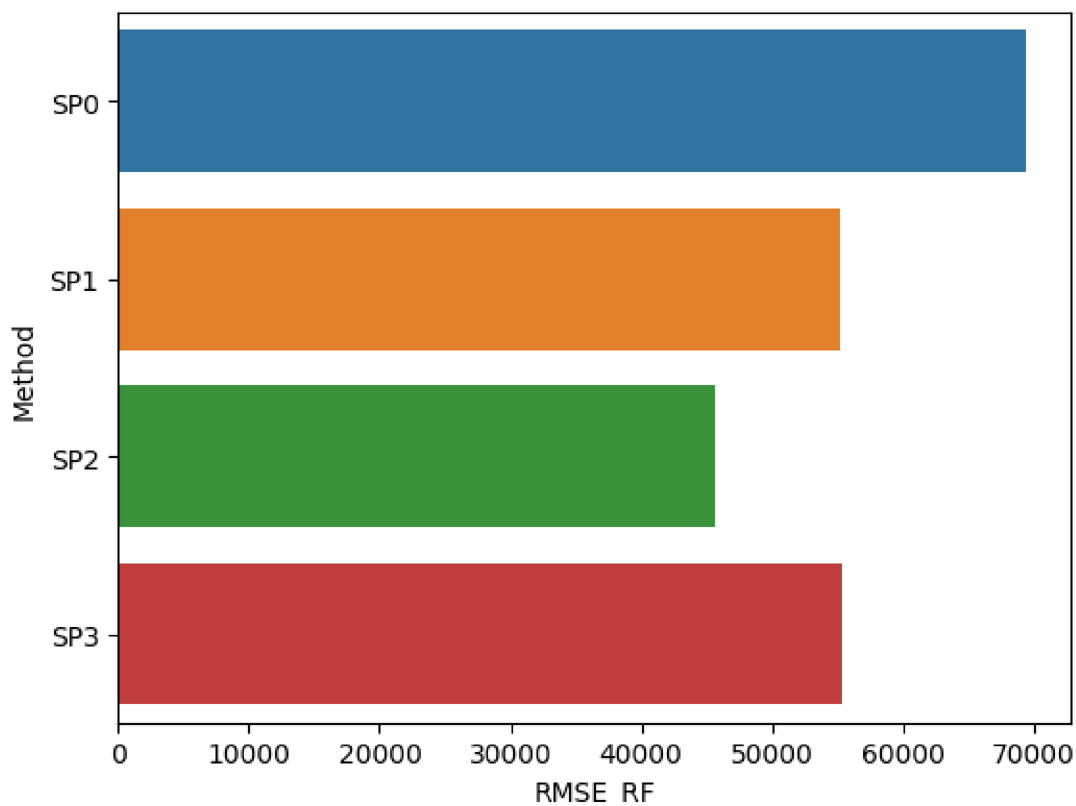
[152]:
```python
#Summary of MAE and RMSE RF
error_summary_RF = {'Method': ["SP0", "SP1", "SP2", "SP3"],
                    'RMSE_RF': [rmse_RF, rmse_RF_SP1, rmse_RF_SP2, rmse_RF_SP3],
                    'MAE_RF': [mae_RF, mae_RF_SP1, mae_RF_SP2, mae_RF_SP3]}#,
                    #'R2_RF': [r2_RF, r2_RF_SP1, r2_RF_SP2, r2_RF_SP3]}
error_summary_RF = pd.DataFrame(error_summary_RF)
error_summary_RF
```

[152]:

	Method	RMSE_RF	MAE_RF
0	SP0	69379.352399	52194.729744
1	SP1	55221.893236	46245.416961
2	SP2	45630.782747	39828.790284
3	SP3	55350.174141	46111.434185

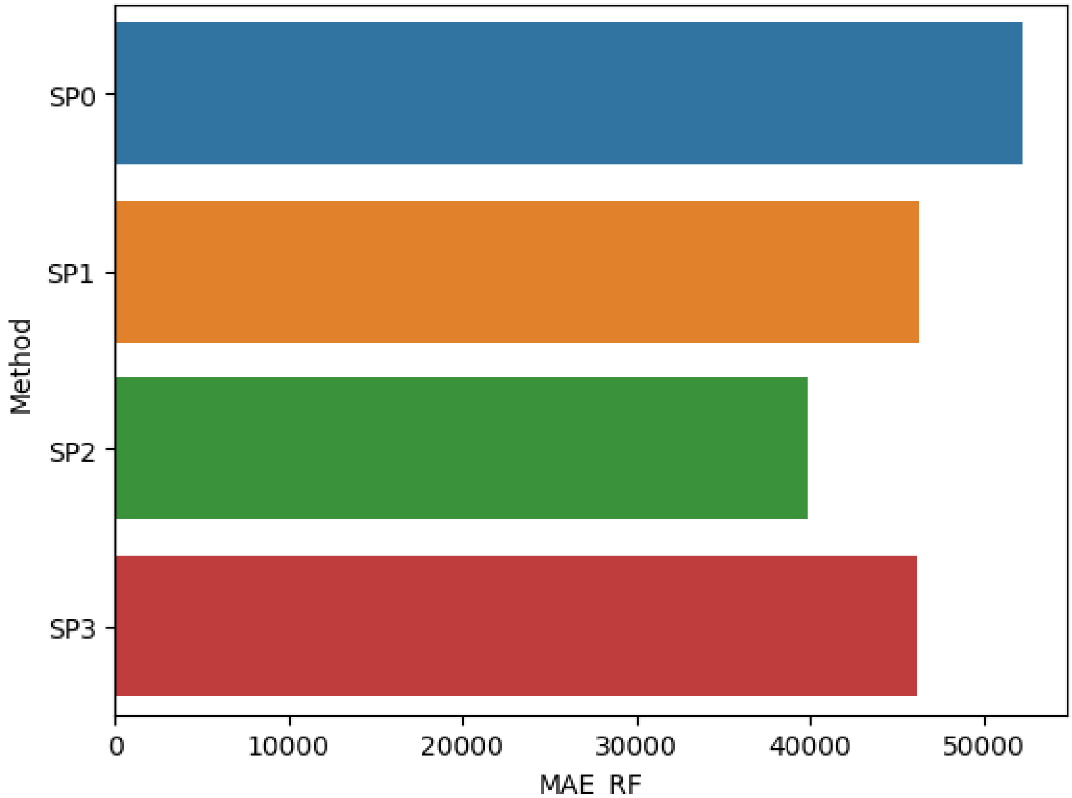
[153]:
```python
sns.barplot(data = error_summary_RF, y = "Method", x = "RMSE_RF")
```

[153]: <Axes: xlabel='RMSE_RF', ylabel='Method'>



[154]:
```
sns.barplot(data = error_summary_RF, y = "Method", x = "MAE_RF")
```

[154]: <Axes: xlabel='MAE_RF', ylabel='Method'>



1.9.2 RF with train test split

[230]:
```
X = train_hpp.drop(columns = ["Id", "SalePrice"], axis = 1)

y = train_hpp['SalePrice']
```

[231]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

[232]:
```
# Inisialization model Random Forest Regressor
rf_regressor = RandomForestRegressor(n_estimators=50)
# Fit the model
rf_regressor.fit(X_train, y_train)
```

[232]: RandomForestRegressor(n_estimators=50)

[233]:
```
# Predicat
y_pred = rf_regressor.predict(X_test)
```

```python
# Evaluate model
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
mae = mean_absolute_error(y_test, y_pred)

# show the result evaluate
print(f'Mean Squared Error (MSE): {mse:.2f}')
print(f'Mean Squared Error (RMSE): {rmse:.2f}')
print(f'Mean Absolute Error (MAE): {mae:.2f}')
```

```
Mean Squared Error (MSE): 587835283.48
Mean Squared Error (RMSE): 24245.31
Mean Absolute Error (MAE): 16497.42
```